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A SYSTEMS APPROACH TO COGNITIVE BIAS INFLUENCES ON STAKEHOLDERS IN THE CIRCULAR ECONOMY

by

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I, Leandi van der Linde, declare that -

The thesis, which I hereby submit for the degree at the University of Pretoria, is my work and has not previously been submitted by me for a degree at this or any other tertiary institution.

I have obtained the applicable research ethics approval for the research described in this work. I have observed the ethical standards required regarding the University of Pretoria's Code of Ethics for researchers and the Policy Guidelines for responsible research.

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Abstract

With Systems Engineering as the compass and Systems Thinking as the guide, this thesis navigates the labyrinth of the Circular Economy and Sustainability frameworks, seeking to unravel the mysteries of decision-making in a complex world. Each page turned is a step forward, a triumph, as you uncover the interconnected threads that weave together the fabric of our society. From the intricacies of sustainable systems to the nuances of human behaviour, this journey is a testament to the power of knowledge and the courage to pursue truth in an ever-changing world.

In the evolving landscape of global economies, reshaped by information technology and digitisation, the relevance of sustainability has never been more pronounced. Amid growing environmental concerns and pressures for sustainability, the Circular Economy emerges as a viable alternative to the traditional Linear Economy, emphasising resource reduction and recirculation. However, decision-making within the Circular Economy is often complicated by the presence of cognitive biases among stakeholders, both internal and external. This thesis explores the intersection of Systems Engineering, Sociotechnical Systems and Circular Economy, aiming to develop a systematic framework that links cognitive biases to unsustainable activities. Through a comprehensive analysis that includes design science research methodology, this research identifies critical leverage points for leveraging biases and enhancing sustainable decision-making. By first conceptualising a few models for sustainable decision-making in the Circular Economy, the study provides development and evaluation measures to give valuable insights to practitioners and policymakers, facilitating the implementation of effective sustainability practices. The findings underscore the importance of understanding and addressing cognitive biases to advance the Circular Economy and promote a more sustainable and equitable global economy.

This research contributes significantly to the field of Systems Engineering and sustainability by developing a novel framework that integrates cognitive biases into decision-making processes within the Circular Economy. By systematically analysing how cognitive biases influence stakeholder decisions, this study provides measurable insights into the barriers and facilitators of sustainable practices. The framework was validated through empirical testing, demonstrating improvement in stakeholder decision alignment with sustainability goals. This integration enhances the predictive accuracy of systems models and offers actionable strategies for practitioners to mitigate the negative impacts of biases, making this research a pivotal step toward more effective and sustainable decision-making in complex systems.

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Keywords: Systems Engineering, Systems Thinking, Circular Economy, Sustainability frameworks, Decision-making, Cognitive biases

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Published conference and proposed journal papers

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2	van der Linde, L. & Benade, S. Circular human sphere–The conceptual development of embedding a social pillar in the Circular Economy framework. EMEA WSEC 2023, 2023. 2-14. https://www.researchgate.net/profile/Leandi-Van-Der-Linde/publication/371226597_Circular_human_sphere_-The_conceptual_development_of_embedding_a_social_pillar_in_the_Circular_Economy_framework/links/6479b03679a7223765085050/Circular-human-sphere-The-conceptual-development-of-embedding-a-social-pillar-in-the-Circular-Economy-framework.pdf
3	van der Linde, L., Pretorius, L. & Oosthuizen, R. Behavioural System Dynamics: Conceptual Integration of Critical Bias Variables into Circular Economy Stakeholder Phases. 2023 Portland International Conference on Management of Engineering and Technology (PICMET), 2023. IEEE, 1-11.
4	van der Linde, L., Pretorius, L. & Oosthuizen, R. 2023. Validating A Behavioural System Dynamic Model To Investigate Bias, Decision-Making Influences In The Circular Economy. International Conference on Industrial Engineering, Systems Engineering and Engineering Management (ISEM 2023).
5	van der Linde, L., Pretorius, L. & Oosthuizen, R. Can Behavioural System Dynamics Uncover Biases in the Circular Economy? South African System Dynamics Conference, November 16-17, 2023 2023 Johannesburg- South Africa. SASD Chapter, 5-18. https://www.researchgate.net/publication/380374003_Can_Behavioural_System_Dynamics_Uncover_Biases_in_the_Circular_Economy
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List of Acronyms and Abbreviations

AHP: Analytic Hierarchy Process
AI: Artificial Intelligence
ASP: Agreement with Sustainable Practices
BC: Behaviour Change
BSD: Behavioural System Dynamics
BSP: Business Sustainability Priority
CB: Cognitive Biases
CBI: Cognitive Bias Impact
CBI2: Cognitive Bias Influence
CC: Belief in Human-Caused Climate Change
CDMT: Circular Decision-Making Tree
CE: Circular Economy
CEMA: Circular Economy Model Adoption
CLD: Causal Loop Diagram
CSR: Corporate Social Responsibility
DSR: Design Science Research
ECR: Environmental and Corporate Responsibilty
EMF: Ellen McArthur Foundation
FFR: Agreement with Fossil Fuel Reduction
HIS: Human Systems Integration
IA: Individual Action
IE: Intersectional Environmentalist
JIT: Just in Time
LE: Linear Economy
LtG: Limits to Growth
MDG: Millennium Development Goals
MI: Media Influence
PA: Agreement with Public Awareness
PDCA: Plan-Do-Check-Act
PDSA: Plan-Do-Study-Act
RC: Resistance to Change
RI: Response to Information
RO: Research Objective
RPD: Recognition Primed Decision
RQ: Research Question
SA: System Archetypes
SD: System Dynamics
SDG: Sustainable Development Goals
SE: Systems Engineering

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SFD: Stock and Flow diagram
SSM: Soft Systems Methodology
ST: Systems Thinking
STMI: Sustainable Technology Management Initiatives
STS: Sociotechnical Systems
TI: Technology and Innovation Impact
OODA: Observe, Orient, Decide, Act
VISIS: Vision-Indicators-System Innovation-Strategy
WH: Willingness to Change Habits
UN: United Nations

List of Definitions

Analytic Hierarchy Process: A structured technique for organising and analysing complex decisions to prioritise cognitive biases and evaluate strategies.
Causal Loop Diagram: A graphical tool used in systems thinking to illustrate the feedback loops and cause-and-effect relationships within complex systems.
Cognitive bias: A cognitive bias is a consistent and systematic deviation from rational judgment or normative standards.
Corporate Social Responsibility: A concept where companies incorporate social and environmental concerns in their operations and interactions with stakeholders.
Debiasing: Reducing negative or opposing bias, particularly concerning judgment and decision-making.
Framework: A structured, conceptual structure to help solve complex problems by organising interrelated elements or components.
Leveraging: The use of resources, tools, or strategies to amplify or maximise the effectiveness and impact of an action or process in a system.
Model: A representation, either physical, conceptual, or mathematical, used to describe and explain the behaviour of complex systems.
PDCA Cycle: A continuous improvement model used in management and engineering, emphasising a cyclical process of planning, doing, checking, and acting.
Soft Systems Methodology: An approach to handling unstructured problem situations by developing models of multiple perspectives.
Sustainable Technology Management Initiatives: Initiatives aimed at integrating sustainability into technology management through practices like AI integration and resource optimisation.

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1. Background to the Research Study

This chapter introduces the research study, providing essential context within the Sociotechnical Systems (STS) framework. The aim is to establish why it is crucial to re-evaluate the Circular Economy (CE) model, considering stakeholders' social impacts and influences.

STS are associated with a holistic approach that considers social and technological impacts. STS originated in the coal mining industry in the 1950s when Trist and Bamforth (1951:3-38) proved that a traditional reductionist approach negatively affects work performance. Transitioning to a CE necessitates a profound understanding of cognitive biases and behavioural dynamics that influence decision-making processes. Existing research underscores the critical role of these biases in shaping sustainability practices, yet there is a significant gap in integrating these insights into CE models. This study aims to close this gap by employing System Dynamics (SD) to elucidate the influences on CE outcomes, providing a comprehensive framework for more informed and sustainable decision-making. This chapter discusses the background of an STS, known as the CE. The research rationale, together with the appropriate roadmaps, is also shared in this chapter.

Imagine a team of engineers working on a complex spacecraft tasked with ensuring its safe journey to Mars. They meticulously design every component, but despite their technical precision, the mission fails because the human operators misinterpret crucial data due to cognitive biases. This thesis draws a parallel to the CE, where the journey toward sustainability is not just a technical challenge but also a cognitive one. Just as a successful space mission requires flawless engineering and clear-headed decision-making, achieving sustainable outcomes in the CE demands a framework that integrates SE with an understanding of human behaviour. This research navigates these interwoven paths, emphasising that addressing cognitive biases is as vital as the technical aspects in guiding stakeholders toward a sustainable future.

1.1. Introduction

Currently, when the globalisation of the economy and its systems are being restructured by information technology and digitisation, STS is more relevant than ever (Stanton, 2022:327-327). Globally, concerns about the environment and other social challenges are increasing, and there is an increased pressure to be sustainable (Haleem et al., 2022:1967). Nevertheless, the development of STSs is not occurring at the same tempo as the current sustainability framework drive, let alone anticipating more pervasive consumerism changes yet to come (Pasmore et al., 2019:67-85).

The CE is one of the sustainability frameworks being used as an alternative to the linear economy (LE). It is a sustainable economic system that emphasises the reduction of raw material extraction and recirculation of resources. Through circularity,

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the system indicates value creation in, for example, the biological and technological industries (Brenes-Peralta et al., 2020:2291).

The decision activities of STS are indispensable building blocks to assessing the different and best sustainable options in a CE. According to Vanson et al. (2022:3-22), several variables and parameters are used in sustainable decision-making, the most relevant being marketing. Generally, marketing may influence consumer decisions through cognitive biases (Gurau, 2015:48+; Kienzler, 2018:86-94; Ho, 2019:773-854). Consumers are rational in principle but many times irrational in practice. Several cognitive biases impact our decision-making. “Our tendency for irrational decision-making is compounded by marketing, which is little more than the art of exploiting cognitive biases”, as stated by Laissue and Kovic (2016:1-29).

As the saying goes, the Stone Age did not end because they ran out of stones (Chu, 2013:1-3). People transitioned to better technology and solutions. The same opportunity lies before us now, with sustainability and the CE. People need to make the correct decisions in our STS before we run out of resources.

1.2. Context of the Research

The ‘where’, ‘who’, ‘what’ and ‘when’ of the research are discussed in this section.

In a CE, stakeholders should make positive leveraged-biased decisions to ensure a thriving, sustainable future. For nearly a decade, the CE has been developed as an inspiring potential to achieve sustainability, but a more holistic view is necessary, as described by James (2022:1-17). The author further elaborates on the need to explore the limiting process's social circles, in the CE. It is limiting because it delimits waste and resources utilising a proposed circular flow but the social aspect is not covered. The ‘where’ of the research is altogether the CE.

The ’who’ of the research gives a sense of the nexus between the ‘where’ and ‘what’. The social stakeholders within the CE and the decision-makers in the environments and systems around the CE are critical to this study. The systemic changes needed to attain a CE and concurrently a more sustainable future lie with these stakeholders.

An imperative part of the study is the SE tools used to manage systems with social elements. As previously mentioned, the social elements connect the CE and the SE. SE identifies, manages, and predicts what changes stakeholders can make to ensure a successful CE. The final context of the ‘what’ includes different SE tools such as systemigrams, archetypes and modelling (Oosthuizen, 2021:1-11).

Another active concern is the ‘when’ of the research. Currently, the CE model is not part of the economic systems of most countries. The model is critiqued as being ideal-

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modern and not realistic. However, we as people are experiencing socio-technical challenges that necessitate realising a model such as the CE (Rask, 2022:1-17). Systemic changes are direly called for; thus, this research is needed.

Sustainability is genuinely a socio-technical challenge currently experienced all over the world.

Existing CE models often fail to account for the human element—precisely, the cognitive biases that significantly impact decision-making. This research uniquely contributes by developing a framework that quantitatively measures these biases and integrates them into SE models. Doing so bridges a gap in the literature and provides a practical tool for stakeholders in the CE, enabling them to make more informed and sustainable decisions. The research outcomes include a validated model that stakeholders can use to identify and mitigate or leverage biases, thus aiming to improve decision-making processes in terms of sustainability outcomes.

1.3. Brief Synthesis of Recent Literature

STS has been theorised and practised before 1960, as mentioned in Section 1 (Emery, 1993:157-186). Different design methods for STS have been researched by Baxter and Sommerville (2010:4-17), who suggest that constructive engagement between the technical and social sides is imperative towards systems development and acknowledgement. Aspirational intensification in technology advancements in recent years demands that STS be re-evaluated. The reason for this is the lack of social advancement despite dramatic economic and technological developments.

In recent literature by Wuyts and Marin (2022:1-18), the authors describe an intersectional environmentalist (IE) approach. IE is defined as a holistic lens that looks at different roles of stakeholders in a CE to understand why some actors exist in certain phases of the CE and what social impact these actors have. Vanhuyse et al. (2021:2-8) also proposed that different categories of stakeholders in the CE have distinct social impacts. This literature will also be used in Section 2.4.1 to understand better which stakeholders in the CE are critical for sustainable decision-making.

The research problem statement objectives and questions are discussed in the following part. The connection between the recent literature discussed, and the following passages are the identification of the individual influences in the complex social system of the CE.

1.4. Research Problem Statement

Preliminary investigation suggests that the social elements within the CE model are biased toward sustainable decisions (Kazancoglu et al., 2020:1-13). This is a

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reasonable proposition for this study and can be proven throughout the research. Biases toward sustainability are preferable in a world where CE can be successful.

Many SE decisions are problematic because they include numerous stakeholders, multiple competing objectives, substantial uncertainty, and significant consequences. Research by Kahneman et al. (2011:50-60, 137) and Leonard and Richard H. Thaler (2008:293) has concluded that cognitive biases can distort stakeholders' decisions. From a CE perspective, these actors exist internally and externally. It becomes imperative to explore, understand and overcome these biases to allow the implementation of innovative models such as the CE to create value for customers, societies, and companies. A research gap in the knowledge of SE, especially SSM, applied to CE decision-making needs to be addressed (Singh and Giacosa, 2019:921-937; Warwick, 2008).

1.5. Research Objectives

To address the problem above, a research project with the following overall objective is proposed: Create an improved sustainably focused system framework by analysing influences on unsustainable and sustainable habits of stakeholders in the CE.

This research aims to develop a systematic framework for the modelling, analysing, and managing decision-making in the CE. The aim is to establish a linkage between cognitive biases and unsustainable activities. The model may then be used to leverage the influences of these biases. The following two research objectives (RO) exist for this study:

- RO1: Identifying areas where control measures are needed to leverage biased decision-making in the Circular Economy
- RO2: Conceptualise a model for sustainable decision-making in the Circular Economy

The results of this research may be valuable to CE practitioners, sustainability programme managers, and stakeholders. The improved model can be used to ensure improved unbiased decision-making. In turn, it means faster, more successful progress towards sustainability, for example, in the CE technosphere and biosphere case illustrated in Figure 1. The possible structural knowledge that can be evaluated comprises identifying the interdependencies and relations between the stakeholder beliefs and the success of the CE.

The social elements also called the stakeholders of the CE, are presented in Figure 1. The stakeholders are divided into two groups: the internal stakeholders, depicted by the blue and grey inner circle, and the external stakeholders, shown in the outermost ring. These elements were identified by van der Linde and Benade (2023:2-14). See Section 3.3.1 for the detailed model development process. The study focussed on

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identifying whether social elements should be part of the formal CE model and which internal social elements fit in the biosphere versus the techno-sphere. The primary objective of this framework is not to establish direct causal connections or links between the CE framework and the social elements. Instead, its purpose is to underscore the existence of numerous internal and external social elements that are intertwined with the CE.

The subsequent diagram offers a visual representation of four key dimensions: (1) the individuals integrated into the CE, (2) their position within the CE structure, (3) the internal versus external categorisation of these individuals, and (4) their involvement in either the techno-sphere or the biosphere.

Specific systemic changes must be accomplished to implement a CE effectively. This is elucidated through the pair of CLDs delineating the influences and relationships among all the constituent elements. Furthermore, the conceptual CE framework delineates the grouped participants within the CE, as depicted in the figure below:

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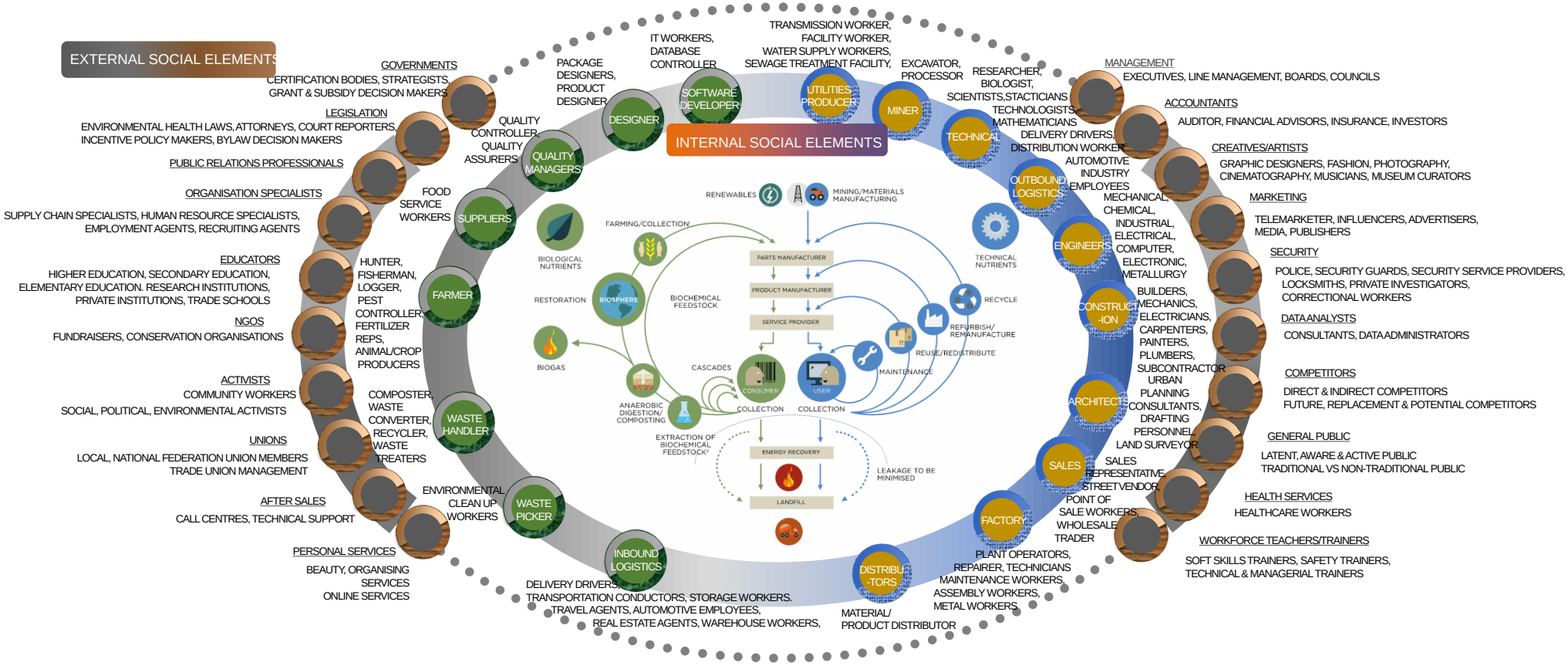

Figure 1. Detailed conceptual CE framework with social elements (van der Linde and Benade, 2023:2-14)

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The research question (RQ2) concerning the integration of internal and external stakeholders within the CE framework is thoroughly addressed in Figure 1. In the following section, all the research questions are discussed. RQ1 is addressed in the following passage, along with the other RQs. The figure introduces the "Circular Human Sphere," a detailed conceptual development emphasising embedding a social pillar into the CE framework (van der Linde and Benade, 2023:2-14). By incorporating social elements, the framework extends traditional CE models, which primarily focus on economic and environmental dimensions, to include human and societal aspects. This holistic approach underscores the significance of stakeholder engagement in achieving sustainable and socially responsible circular systems.

Moreover, the framework demonstrates that internal and external stakeholders are pivotal in the operationalisation and success of CE initiatives. Internal stakeholders, such as employees and managers, are crucial for implementing CE practices within organisations, ensuring adherence to sustainable processes, and fostering a culture of innovation and responsibility. External stakeholders, including customers, suppliers, and policymakers, play an essential role in shaping market dynamics, regulatory frameworks, and societal expectations. By highlighting these roles, the conceptual CE framework and its social elements showcase how stakeholder collaboration and alignment are essential for driving systemic change towards a more sustainable and inclusive economy. Thus, Figure 1 effectively answers RQ2 by elucidating the critical involvement of various stakeholders within the CE framework and demonstrating their interdependencies through a comprehensive CLD. The process of developing Figure 1 is further discussed in Chapter 3, Section 3.3.1. The answer to the research question is expanded on in Chapter 9.

Each one of the stakeholders presented in the CE model above makes decisions. The crucial need is to ensure these decisions are sustainable and environmentally focused, with the least unintended consequences possible. The following subsections describe the research questions, contributions, and limitations of the current doctoral research project.

While some technical cycles are slow, such as plastic life cycles, other biological cycles take centuries, such as carbon generation and utilisation. Ultimately, the responsibility for the crucial endeavour of rejuvenating natural systems and establishing regenerative material flows rests solely with humans. This figure has demonstrated the potential of employing ST, Human-System Interaction (HSI), and studies in organisational behaviour to dissect complex systems like the CE. Of paramount importance is the discovery of complex interactions and relationships among human actors within the CE, as depicted in the conceptual framework in Figure 1.

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In conclusion, this research will comprehensively address the stated objectives. RO1 will identify critical areas requiring control measures to leverage biased decision-making within the CE. Concurrently, pursuing RO2 will result in the conceptualisation of a robust model for promoting sustainable decision-making within the context of the CE. These accomplishments will advance our understanding of this complex system and provide crucial insights into cultivating more equitable and environmentally conscious practices in economic decision-making.

1.6. Research Questions

The questions asked in this study to reach the objectives discussed above are:

- RQ1: To what extent are biases prominent in sustainable decision-making?
- RQ2: To what level do internal and external stakeholders fit into the Circular Economy framework?
- RQ3: How greatly do biases influence the need for sustainability in the CE?
- RQ4: How does the adoption of Circular Economy practices influence stakeholder dynamics, and what are the causal relationships involved?
- RQ5: How extensively can Behavioural System Dynamics (BSD) uncover, validate and address biases in the Circular Economy through empirical survey data?

In Table 1, the research questions are explored further with details about relevance, insight into the question, and how feasible it is to get an answer. Table 36 shows the relation between the research questions and objectives in the previous section. RQ1 captures bias as an existing factor, while RQ3 investigates the impact of bias on sustainability perceptions and needs within the CE framework.

In conclusion, exploring these research questions promises to unveil crucial insights into the decision-making dynamics within the CE. By delving into RQ1, the research will pinpoint how much biases influence decision-making processes. RQ2 shed light on the distribution of decision-making power between external and internal stakeholders in the CE. Addressing RQ3 will lead to the proposal of leverage points to biases within the CE. Furthermore, by examining RQ4, the research will identify the causal relationships between cognitive biases and stakeholders' decision-making within distinct CE phases. RQ5 will highlight the CE influences. The culmination of these inquiries will contribute substantial knowledge to the field, guiding the development of more informed and equitable decision-making practices within the CE. In the following section, the rationale for the questions above is discussed.

These research questions are answered in the following sections of this study. The approach was to compile several conference and journal papers as part of the final doctoral thesis to respond to and evaluate the answers, in part as shown in Figure 2.

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Table 1. Research questions explained applicable to this study.

RQ	Relevance	Insight	Feasibility
1	Recent studies have proven or indicated that improved decision-making methods and models within the CE are needed (Bacher et al., 2018:1; Brenes-Peralta et al., 2020:2291; Gimeno et al., 2020:68-69; Vanson et al., 2022:3-22).	This study will take it further and investigate the most prominent biased decisions. Typically, biased choices will be identified and evaluated further.	The first research question can be answered through a thematic literature analysis of current and future predicted decision-making models.
2	Literature differentiates where the most impactful power lies in the CE. Some research indicates it is external and should be governed by law, for example, and others refer to the internal consumers controlling the flow of the materials (Mikichurova and Vlialko, 2021:012022; Hu et al., 2018:990; Evans et al., 2017:1396-1411).	Awareness of the stakeholders with the most power over the model will determine where leverage points are needed.	A thematic analysis will be done with Atlas.ti to distinguish which group, internal or external, influences the overall CE model implementation more. Leverage points for these groups will be evaluated in another research question.
3	Systems engineers and social scientists have concluded that people tend to make irrational decisions. Studies exist exploring possible mitigations for certain biases (Morewedge et al., 2015:129-140; Barton et al., 2016; Felmban, 2015).	The influences on the need for sustainability in the CE can be identified. It is crucial to implement and change a system.	A conceptual model will be developed to show how decision-making is part of the current CE model framework. The biased influences will be identified according to the answers to the research questions. SD simulations will be used to show the influence of decision-making on sustainability.
4	CE adoption and cognitive biases are exceptionally researched in social sciences. This study's importance lies within the most common biases found in the literature (Wilke and Mata, 2012:531-535; Wiers et al., 2020:231-241).	The causal relationships identified will be modelled to understand the positive or negative impact on the ability of the decision-maker to make sustainable choices.	The research will use survey data from respondents in certain CE phases and different stakeholder roles.
5	The CE consists of several stages or loops. The model is seen as a catalyst toward sustainability. The technosphere within the CE model consists of numerous stages such as re-use, remanufacture, recycling, etc. (Schröder et al., 2018; Valverde et al., 2021:12652).	The different stages of the CE lend themselves to different intervention places where decisions are made. As specified in SE, the pre-requirement for a model is crucial at the beginning of a project. Realistic data will give insight into which stages need changes.	The last research question can be answered through design science research methodology and analysis of the survey data.

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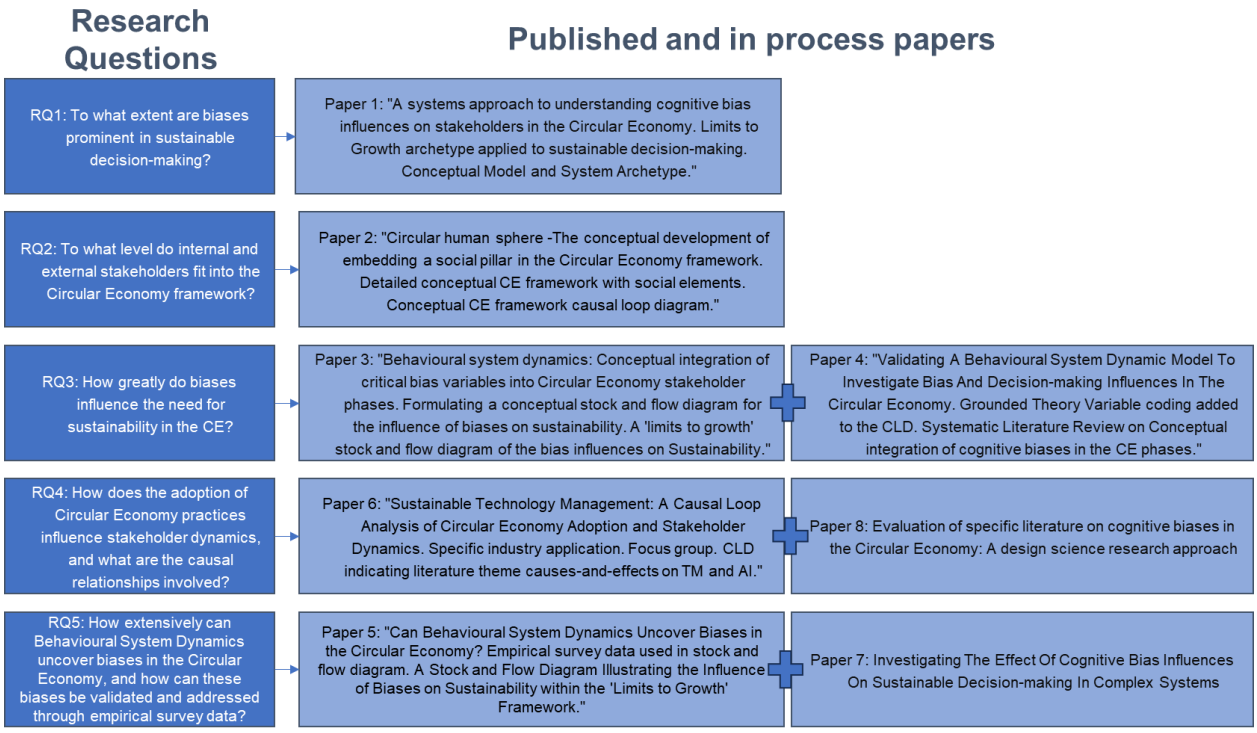

Figure 2. Research questions vs answers from published and in-process papers

1.7. The Rationale of the Research

From a methodological perspective, current design approaches used in CE research often treat stakeholders as passive actors intending to generalise and aggregate individual responses (Alfred et al., 2017:1706-1710; Chiappetta Jabbour et al., 2020:110416). In other words, variance across individuals is usually ignored. The novelty in this research is the application of ST, which takes the messy arguments of the natural world caused by people having different perceptions and creates defendable and rational models for comparison with what is happening in the real world. This will help make judgments or recommendations regarding the response to the issue or problem (Shu and Bazerman, 2010).

The following extract comes from the acclaimed yet controversial 48 Laws of Power book (Greene, 2000). Law 38 reads: “Think as you like but behave like others”. The author explains that when people go against the norm, they challenge other peoples’ beliefs and cultures. He warns that this must not be done impudently because it might offend others.

Why do numerous management guidebooks available today, such as How to Win Friends and Influence People from Carnegie (2017:118-126), The Seven Habits of Highly Effective People by Stephen R. Covey (Armocida, 1992:120-121), and The Purpose Revolution: How Leaders Create Engagement and competitive advantage in an age of social good by Izzo and Vanderwielen (2018:240), all mention that we should

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not challenge our own biases, but rather fit in with the crowd? In effect, Borland et al. (2016:293-307) have claimed that the most recent management literature does not focus on the environment. Many managerial principles are misaligned toward sustainability. According to the latest United Nations (UN) report, this crowd we are trying to fit in are part of some of the worst polluters in history - despite short-lived pandemic reductions (United Nations Department of Economic and Social Affairs, 2022:119-220). The importance of this study stems from the realisation that without changing our unsustainable habits, sustainability may be just a pipe dream.

Doyle et al. (2008:269-294) provide consideration in their research that mental models play a crucial role in improving complex systems decision-making. Consequently, understanding the feedback processes through SD and ST is critical.

1.7.1. Theoretical Rationale (Scientific relevance)

Understanding and evaluating the relationship between SE and CE will contribute to theory by showcasing the interconnections between systems modelling and sustainability. It will contribute to visualising the leverage points for a successful CE with the assistance of SE tools. This study can be used as a reference for future research combining these components. Secondly, this study contributes to complex system literature by indicating that system methods exist to improve the interpretation and implementation of sustainability. Other sustainable models can include systems methodologies used and researched in this study. This study will contribute to the approach taken in evaluating the CE model and its stakeholders. Methods to improve the success of a CE can be adjusted according to the focus areas identified in this study.

1.7.2. Practical Rationale (Societal relevance)

In practice, this study can identify and leverage common biases in the sustainability arena and different management arenas. Evaluations of biased stakeholders within a CE can be completed using this study's methods. The focus is not on either supportive or damaging biases but both. Instead of focusing on a single bias and its influence on sustainable decision-making, this study will assess several biased influences on certain phases of the CE.

1.7.3. Significance of the Research

The significance of this study lies in its exploration of the complexities and biases inherent in sustainable decision-making, particularly within the CE framework. By examining the prevalence of biases that affect sustainability choices, the study provides critical insights into the cognitive and structural barriers that impede effective decision-making. Furthermore, it highlights the crucial roles of both internal and external stakeholders in implementing CE practices, showcasing how their engagement and interactions are essential for success. The investigation reveals how

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biases influence the drive for sustainability within CE initiatives, emphasising the need for conscious efforts to leverage these biases. Additionally, the study underscores the potential of BSD to uncover and analyse these biases through empirical data, offering actionable insights and strategies for validation and leveraging. Overall, the Design Science Research (DSR) approach will illustrate the findings as a nuanced picture of how biases and stakeholder dynamics impact the adoption and effectiveness of CE practices, providing valuable guidance for policymakers, organisations, and researchers aiming to foster a more sustainable and equitable economy.

1.8. Structure of the Following Chapters

The structure of this thesis follows the systematic and iterative approach of the DSR methodology, chosen for its inherent suitability in addressing complex problems through the creation and evaluation of innovative artefacts. DSR offers a robust framework that aligns seamlessly with the iterative nature of the research process, allowing for multiple cycles of design and refinement. In adopting the DSR format, this thesis acknowledges the dynamic and evolving aspects of the research journey.

Each chapter corresponds to a specific phase of the DSR methodology, providing a structured exploration of problem awareness, solution suggestion, development, evaluation, reflection, and communication. The iterative cycles inherent in DSR facilitate the design artefact's improvement and contribute to the evolution of design principles, ensuring a holistic and thorough investigation into the research problem. This format, grounded in DSR, enables a more comprehensive understanding of the intricacies of designing and evaluating innovative solutions, making it an ideal choice for tackling multifaceted challenges through successive improvement and learning cycles.

Figure 3 illustrates the DSR methodology in relation to the chapter. In Chapter 1, the background of the research study was discussed. This included the context of the research in an STS and why it is vital, according to recent literature, to re-evaluate the CE model to integrate the social impact and influences of stakeholders within the system.

Chapter 2 elaborates further on Chapter 1, with literature about sustainability, SE and cognitive biases. Beginning with the awareness of the problem from the DSR methodology, the research delves into a comprehensive review of existing literature and engages stakeholders to articulate and define the intricacies of a real-world problem or opportunity. Current models and theories are described, and the importance thereof is elaborated on. The motivation of the chapter is to explore existing methods and models for topics found in literature and to identify how these can be interconnected and synthesised for the following chapters.

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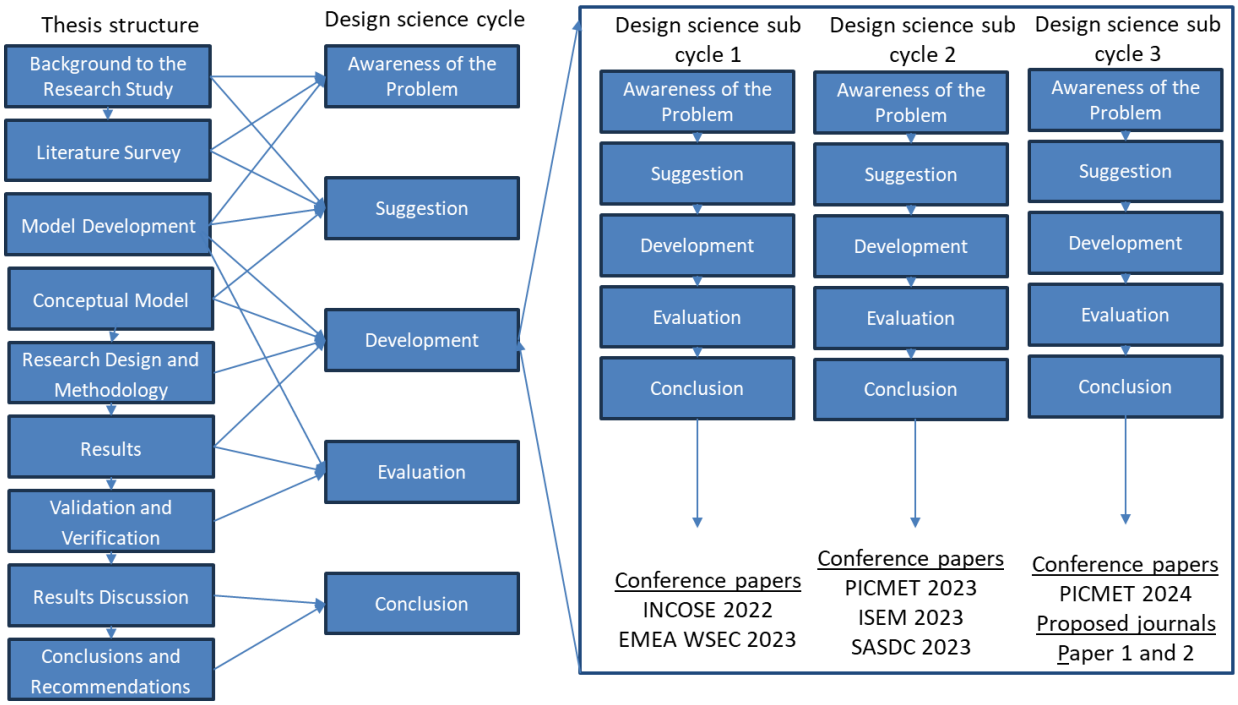

Figure 3. DSR is applied to chapters based on conference and journal papers.

Chapter 3 provides a comprehensive account of the development of various models central to this research. The models are essential for understanding the complex interactions within the CE and for analysing the impact of cognitive biases on decision-making processes. The chapter systematically details the methodologies, theoretical foundations, and data used to develop each model and explains how they interlink to form a cohesive research framework. The chapter begins by outlining the model development process through a DSR methodology applied in subcycles throughout the chapter. This structured approach ensures the models are well-integrated with the broader theoretical context and aligned with the research objectives. This chapter thus sets the stage for the conceptual model presented in the subsequent chapters.

In Chapter 4, it is established that a theoretical model for sustainable decision-making can be conceptualised based on the literature and findings gathered in the previous chapters. This conceptual model is developed through boundary definitions, different systems approaches, and methods. Finally, the chapter concludes with a tangible model. The following chapters will create the model further with the research methods and data gathered. This step, the suggestions from the DSR methodology, involves the creative proposal of a novel solution backed by the development of conceptual models or frameworks.

Chapter 5 discusses in more detail the research methods used in the study. Firstly, the strategy and DSR methodology are addressed. A detailed description and evaluation of the surveys are discussed, and a summary of the research design is given. As the

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process advances to development, the focus shifts to the tangible creation of the proposed artefact, be it a system or a model, utilising established design principles and methodologies.

Chapter 6 presents the data and analysis from the methods discussed in Chapter 5. A comprehensive account of the data-gathering process is provided with a summarised version of the gathered data. The data analysis section of this chapter is the rational focus of the study. Different data analysis methods are discussed and applied in this chapter and validated in the next section. Moving forward, the evaluation step from the DSR methodology scrutinises the artefact's effectiveness and efficiency, entailing the establishment of evaluation frameworks and the execution of empirical studies or simulations.

In Chapter 7, the data validation and verification are done through comparison. The final model is compared to the conceptual model of Chapter 4. The differences and similarities are discussed and analysed to conclude with a final model for a social-debiased CE model. Reflection ensues, inviting a critical analysis of the design and evaluation process, identifying strengths, weaknesses, and areas for enhancement. The reflective insights gleaned feed into the refinement of both the artefact and the underlying design principles.

Subsequently, Chapter 8 is the communication step of the results, disseminating the research results to the academic community and practitioners through scholarly publications and presentations at conferences or workshops. The development of the final thesis expanded from these.

The ensuing section, Chapter 9, concludes the discussion of the results with explanations for further use of the model. The limitations and assumptions relevant to the research are discussed and explored to validate the study in the context of the preliminary decisions taken by the research. Future studies pertinent to expanding this research are discussed in this chapter before the study's conclusion.

Integral to the entire process is recognising the iterative nature of DSR, as seen in Figure 4, emphasising that each cycle informs subsequent iterations, fostering continuous improvement. Moreover, active engagement with stakeholders remains a pivotal aspect, ensuring the designed artefact aligns with real-world needs through collaboration and ongoing feedback. Upholding ethical standards throughout, the methodology concludes by underscoring the importance of ethical considerations in safeguarding the integrity of the research. The structured progression of these steps facilitates a holistic exploration of multifaceted challenges and positions DSR as an adaptable and practical methodology for navigating successive cycles of design, refinement, and scholarly contribution.

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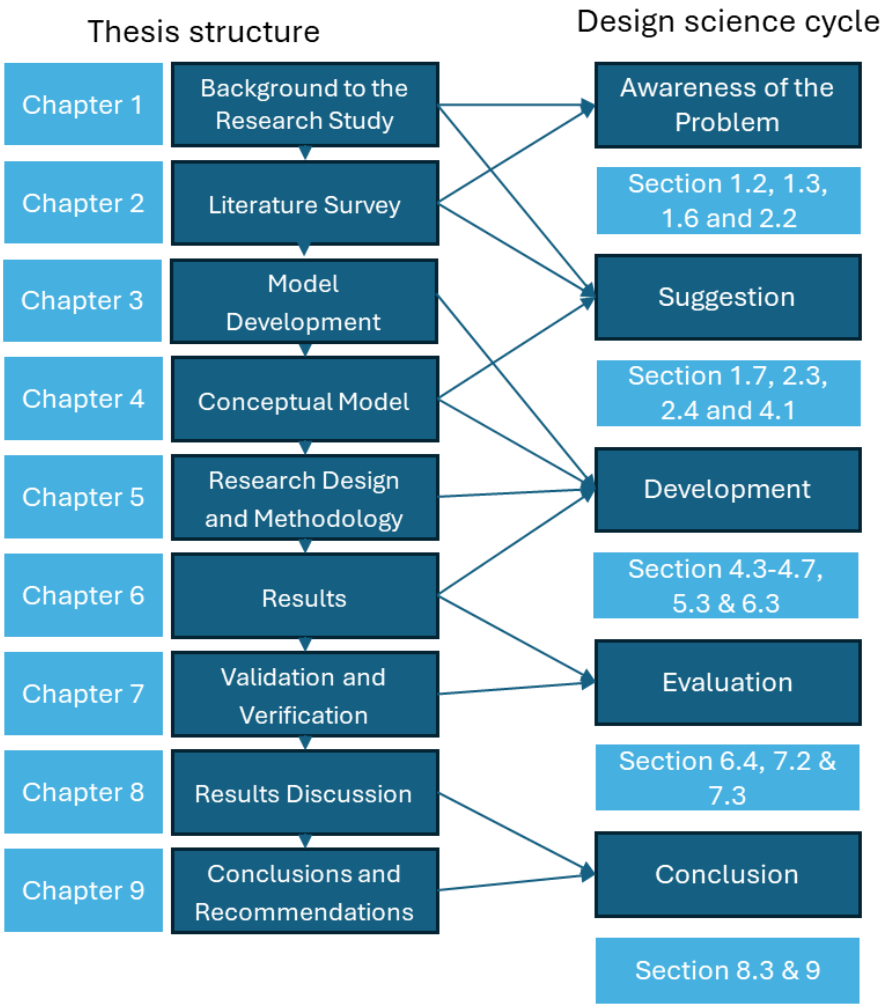

Figure 4. Design Science Research Framework - applied to thesis structure

1.9. Research Roadmap

This section details the research approach, the methods used, and the research design. The proposed research strategy for this study is shown in Figure 5.

The research roadmap provides a clear and structured overview of the study's progression, highlighting key milestones and methodological decisions. It guides the reader through the research process, demonstrating how each phase contributes to the overall objectives. By outlining the rationale behind pivotal choices and the timeline followed, the roadmap ensures transparency and helps contextualise the findings within the broader scope of the research.

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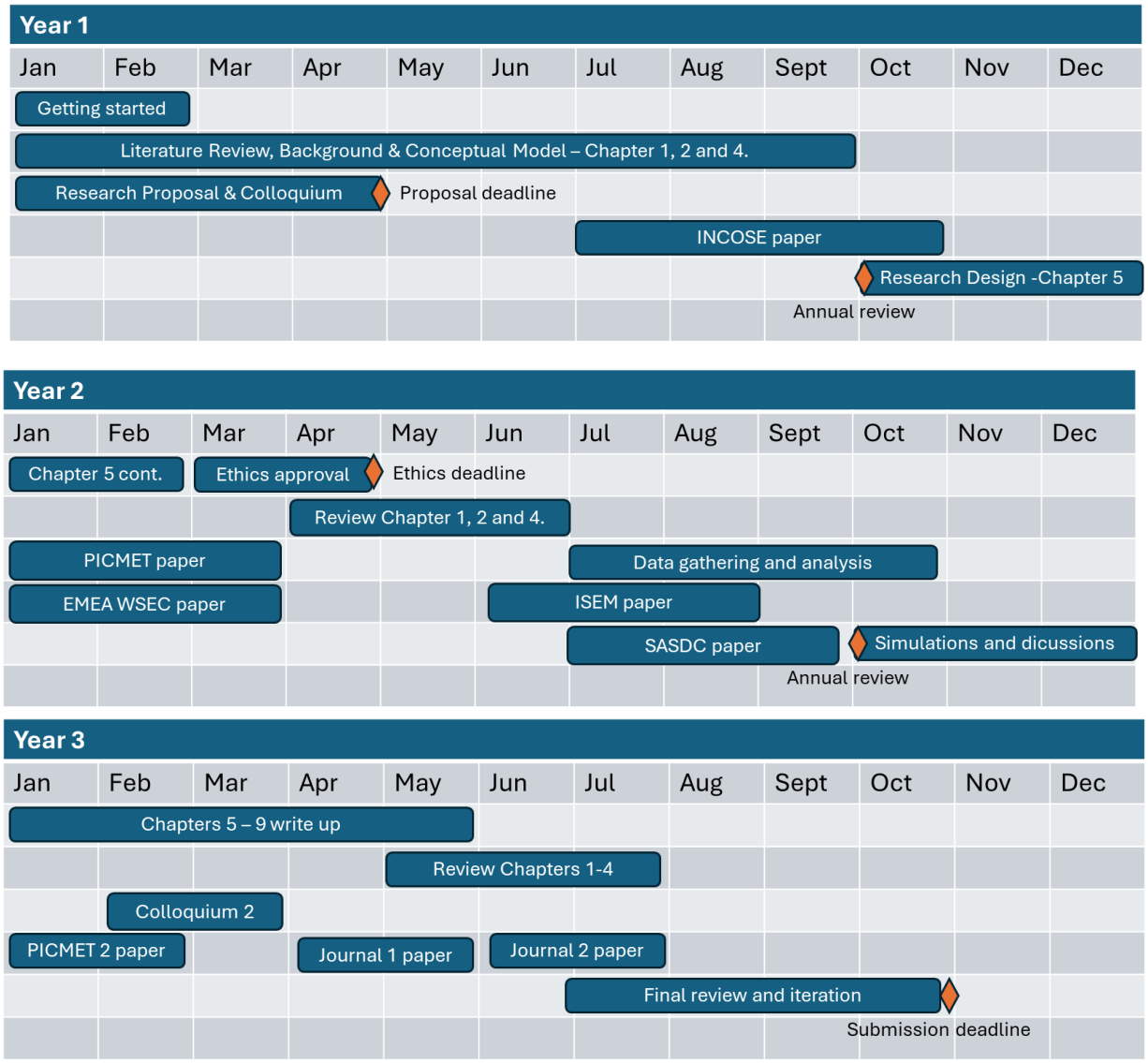

Figure 5. Proposed schedule of the research study in GANTT chart format

While developing this thesis, several research papers were written and published, each contributing to the overall framework and findings presented here. These papers serve as key building blocks in the progression of the research, providing detailed discussions on specific methodologies, models, and results while addressing various aspects of the core research questions. By embedding these individual studies within the structure of this thesis, a cohesive and comprehensive understanding of the research is achieved.

Each paper was developed in alignment with the DSR methodology, which forms the foundation of the thesis. The DSR framework is utilised to guide the iterative development of conceptual models, allowing for continuous refinement based on empirical findings and theoretical advancements. The methodologies, findings, and discussions from these papers are systematically incorporated into the thesis, with detailed sections exploring the specific methods employed in each study. These

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include the research's design, implementation, and evaluation phases, all contributing to the overall DSR process outlined in this work.

To ensure clarity and coherence, the discussions and analyses presented in the individual papers are integrated into the broader thesis narrative, summarised and linked to the overarching research objectives. This approach not only strengthens the methodological rigour of the thesis but also provides a clear, step-by-step progression of the research, illustrating how each study fits into the overall framework.

The results and insights gained from these papers are thus interwoven throughout the thesis, contributing to a well-rounded exploration of the research questions and ensuring that the thesis presents a thorough and methodologically sound investigation.

1.10. Chapter Summary

This chapter presented background information on the need for this research and the necessity of a debiased CE. This chapter highlights the importance of integrating social dynamics into the CE model by examining recent literature. It sets the stage for the subsequent chapters by outlining the research problem and objectives. This introduction sets the foundation for the iterative research cycles in DSR, where each conceptualisation, development, and validation phase constitutes a significant research effort. This section fits into the DSR framework of the thesis, as shown in Figure 6.

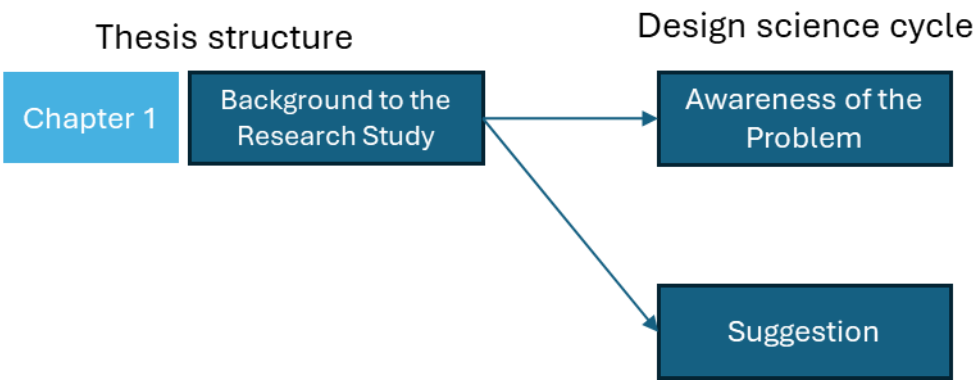

Figure 6. Design Science Research Framework - Chapter 1

By looking into the mirror and seeing the future generations that our decisions will influence, the question remains: “How will my biased decisions influence the sustainability of the world?” This study will identify these realisations that can be applied to ensuring sustainable choices crucial for a successful CE.

In essence, C. West Churchman word’s remains true: “Systems thinking starts when you first see the world through the eyes of others”, and these eyes are the current decision-makers as well as the eyes of the future generations (Matthews, 2005:165-

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212; Miller, 1969:288-291). Since we live on a planet borrowed from our children and inherited from our ancestors, it is critical in this instance to understand and apply ST to the CE. This thesis intends to shed light on the need for analytical thinking in sustainability.

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2. Literature Survey

How do we construct a battle plan for the war against unsustainability? We start with assembling an army of people equipped with the correct weapons. This chapter discusses the people needed for this enormous task and which weapons are required to overcome the enemy. Section 2 expands on the background provided in Section 1 by delving into the literature on sustainability, Systems Engineering (SE), and cognitive biases. It begins with problem awareness from the Design Science Research (DSR) methodology.

2.1. Introduction

Consider the process of designing a new transportation system for a bustling city. Engineers use ST to map out every route, but the system could fail to reduce traffic or emissions if they ignore how people make travel decisions—often based on habits and biases rather than logic. In this chapter, the research explores the existing literature to establish how SE, cognitive biases, and CE are deeply interconnected. While SE provides the technical map, cognitive biases represent the unpredictable human elements that can derail even the best-designed systems. By reviewing how these factors interact, the research builds a case for a holistic approach that blends technical rigour with an understanding of human behaviour to drive sustainability in the CE. The literature survey serves a crucial role in the awareness phase of the DSR cycle. This phase is essential for identifying and articulating the problem space, which forms the foundation for the subsequent model development in this research.

This section fits into the DSR framework of the thesis, as shown in Figure 7.

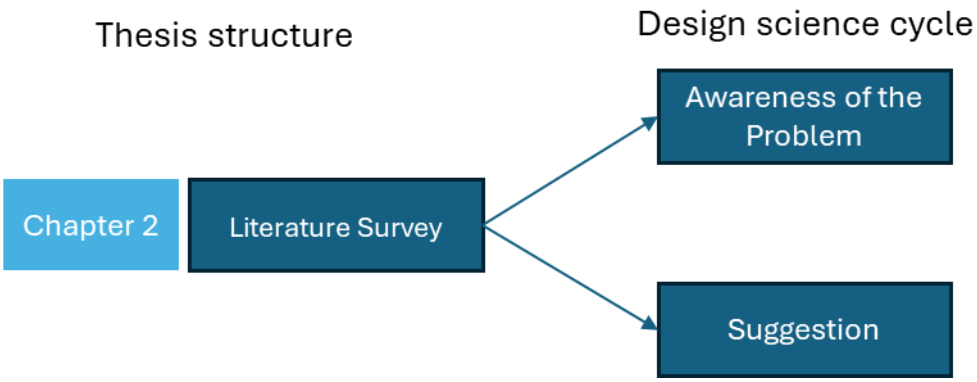

Figure 7. Design Science Research Framework - Chapter 2

Recently, It has been proven that transformation is possible if a critical mass of people supports a change (Fletcher and Griffiths, 2020:102185). The COVID-19 pandemic showcased how necessary it is for people to take charge of their decisions and influences for the greater good (Bavel et al., 2020:460-471). Support systems such as communication networks and resources also proved crucial when transformation is needed (Plekhanov et al., 2022:2-19).

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2.2. Detailed Literature Review

The importance of a literature review lies in the fact that a large amount of research is published daily, and organisation and comprehension of topics are needed to grasp the subject matter adequately. In other words, a literature review is research on research.

Figure 8 summarises the approach taken in this literature review to ensure the reliability of literature and sources and only to include the most relevant information on the chosen subjects. The three parts discussed at every step are categorised as follows: The bullet point is the objective of the step, the star is the hold and review point, and the arrow is the decided direction to get to the aim.

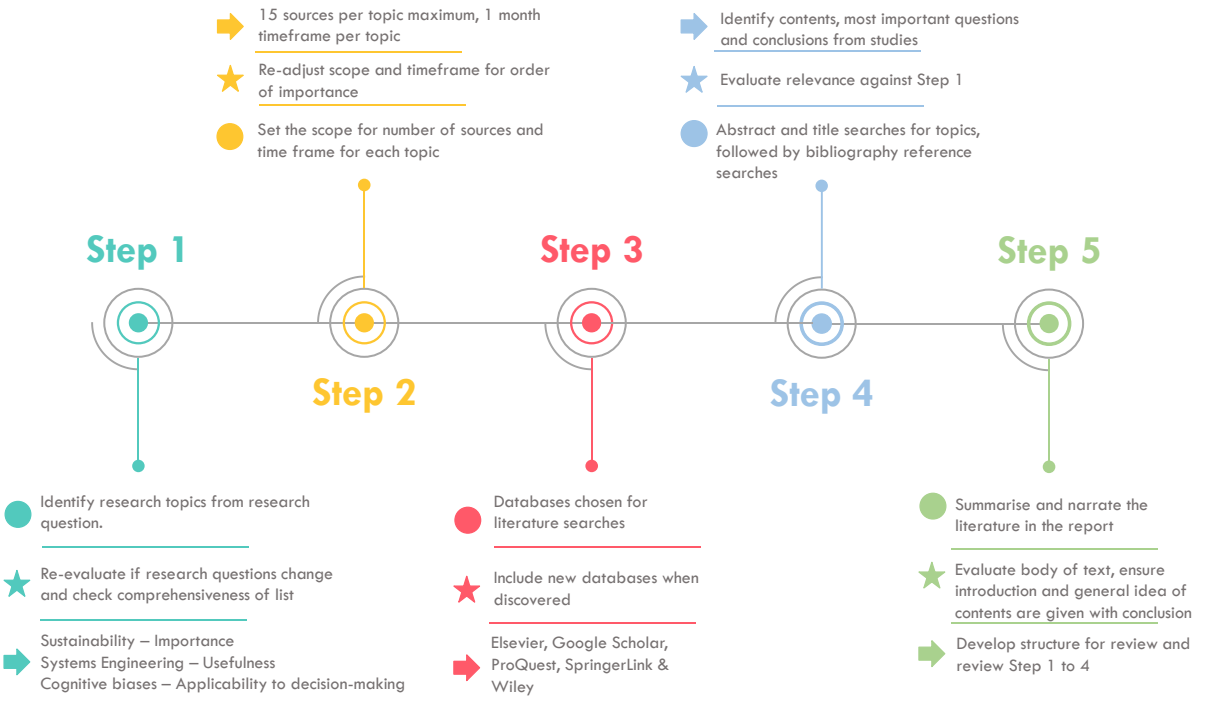

Figure 8. Literature review method and hold points discussed - Adapted from Denney and Tewksbury (2013:218-234)

2.2.1. Background of Sustainability

In scientific terms, sustainability means the state of indefinite existence (AtKisson, 2006:231–243). The previously referenced author, Alan AtKisson, started working as a professional on sustainability in the late 1980s. He pioneered in this field and became the executive director of the In Context: A Quarterly of Humane Sustainable Culture journal. The UN recognised his sustainable initiatives, one of which is the "sustainability change agents" theory. Change agents promote and support a new model or framework within a system (Gallagher et al., 2020:181-195). Sustainability change agents are needed across every element of every system.

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Another invaluable tool developed by Alan AtKisson is the VISIS method. This is an acronym for Vision, Indicators, Systems, Innovation and Strategy (AtKisson, 2011). In Figure 9, sustainability is discussed in the VISIS method.

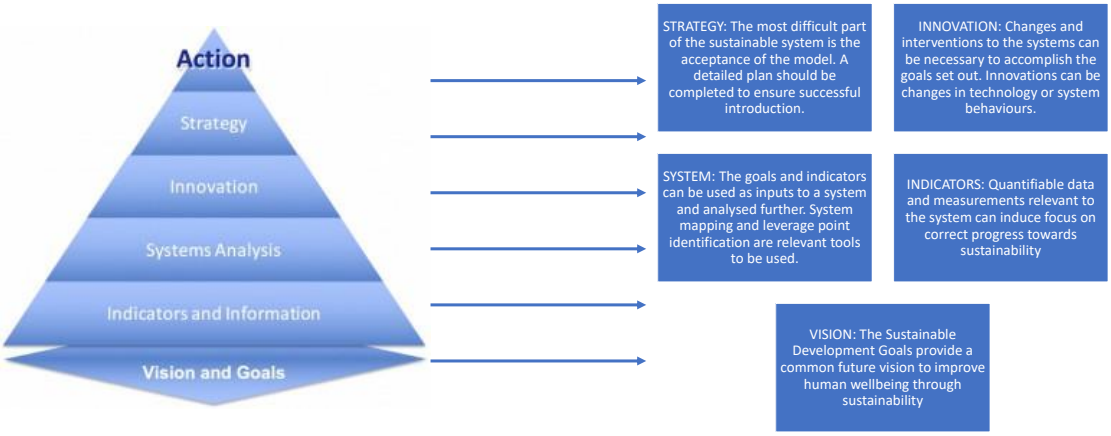

Figure 9. VISIS method for sustainability - Adapted from AtKisson (2011:23-42)

The VISIS method is grounded on a standard and detailed vision. The pinnacle of the rest of the process depends on understanding and aiming towards a universal goal. As mentioned in Figure 9, one of the sets of common goals already adopted by several countries includes the SDGs.

The United Nations Sustainable Development Goals (SDGs) were officially documented in 2015—the initial recognition of SDGs aimed to transform the world with an agenda for sustainable development by 2030. Before the SDGs, Millennium Development Goals (MDGs) were set out in 2000 to address and reduce extreme poverty and hunger in essentially less developed countries. On the other hand, the SDGs are more inclusive, with seventeen (17) different agendas and more than 150 sustainable targets. These cover a broader scope of sustainability challenges experienced by developed and developing countries (Arora and Mishra, 2019:339-342).

Further, the topic of sustainability can alternatively be represented by the three pillars of development. The three pillars are 1) Social, 2) Environmental, and 3) Economic, and they signify the equally important support function of each pillar. This research study focuses on the social pillar of sustainability. The study focuses exclusively on the social pillar of sustainability because it aims to explore the complex dynamics of decision-making processes influenced by cognitive biases within the CE framework. While the environmental and economic pillars of sustainability are crucial in developing comprehensive sustainability strategies, the social pillar addresses the human and organisational factors that significantly impact the effectiveness and implementation of these strategies.

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Reasons for focusing on the social pillar:

- Understanding human behaviour and decision-making: The social pillar encompasses the human elements of sustainability, including social equity, community engagement, and stakeholder participation (Liu et al., 2023:826-849). This study investigates how cognitive biases—systematic patterns of deviation from norm or rationality in judgment—affect decision-making processes. Focusing on the social pillar, the research aims to understand how human cognition and behaviour can hinder or enhance the CE's sustainable practices. The study investigates the influences between the pillars further to suggest the hierarchy and layered connections between them.
- Relevance to organisational and societal change: Social sustainability is crucial in fostering organisational and societal change towards more sustainable practices (Sondh et al., 2024:101337). The study aims to identify and analyse the role of various stakeholders (e.g., policymakers, industry leaders, community members) and how cognitive biases shape their decisions. This understanding can help develop strategies to mitigate biases, promote fair and inclusive decision-making, and encourage behaviour change towards sustainability (Cordella et al., 2023:3-8).
- Interdependence with environmental and economic pillars: While the study focuses on the social pillar, it does not entirely exclude the environmental and economic pillars. The social dimension is deeply interconnected with environmental and economic aspects (Roos, 2024:253-338). For instance, decisions influenced by cognitive biases can have significant environmental impacts (e.g., neglecting sustainable resource use) and economic consequences (e.g., undermining long-term profitability due to short-term thinking) (Enke et al., 2023:818-832). By focusing on the social pillar, the study indirectly contributes to understanding how enhancing social aspects can lead to better environmental and economic outcomes.
- Addressing a gap in the literature: Much of the existing research on sustainability within the CE focuses on environmental and economic dimensions, such as resource efficiency, waste reduction, and cost-benefit analysis (Nikolaou et al., 2021:1-20). A relatively smaller body of work examines the social aspects, particularly the cognitive and psychological factors influencing decision-making (Skene and Murray, 2015:480). This study addresses this gap by concentrating on the social pillar, contributing to a better understanding of sustainability.
- Implications for policy and practice: Insights derived from focusing on the social pillar can inform policies and practices that promote more inclusive and effective decision-making processes (Sharifi et al., 2024:1-15). Understanding cognitive biases and their effects on sustainability decisions can help design better interventions, training programs, and policy frameworks that foster social sustainability and, consequently, better environmental and economic practices (Schröder et al., 2020:1-9).

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Focusing on the social pillar, this study provides a unique perspective on sustainability that complements the more commonly explored environmental and economic dimensions. It emphasises the importance of human behaviour and decision-making in achieving a truly sustainable CE.

In Table 2, a summary of the SDGs is given, along with the corresponding MDGs and how they relate to the pillars of sustainability. In the ensuing paragraph, the pillars are linked to the CE.

Table 2. Links between SDGs and MDGs with applicability to pillars of development - Adapted from (Díaz-López et al., 2021:1-17; Kumar et al., 2016:1-4)

Sustainable Development Goals	Millennium Development Goals	Pillars of Development
1. No poverty	1. Eradicate extreme poverty and hunger	Social and economic
2. Zero hunger		Social
3. Good Health and Well-being	4. Reduce child mortality 5. Improve maternal health 6. Combat HIV/Aids, malaria and other diseases	Social
4. Quality Education	2. Achieve universal primary education	Social
5. Gender Equality	3. Promote gender equality and empower women	Social
6. Clean Water and Sanitation	7. Ensure environmental sustainability	Social and environmental
7. Affordable and Clean Energy		Economic
8. Decent Work and Economic Growth	No direct link	Economic
9. Industry, Innovation and Infrastructure	No direct link	Economic
10. Reduced Inequality	No direct link	Social and economic
11. Sustainable Cities and Communities	No direct link	Social
12. Responsible Consumption and Production	No direct link	Social and economic
13. Climate Action	No direct link	Environmental
14. Life Below Water	7. Ensure environmental sustainability	Environmental
15. Life on Land		Environmental
16. Peace and Justice Strong Institutions	No direct link	Social
17. Partnerships to achieve the Goal	8. Global partnership for development	Social

The Ellen MacArthur Foundation (EMF) was founded in 2010, and the founder, Dame Ellen MacArthur, created a framework for the CE (EMF, 2017). This framework, with two pertinent elements - the biological and technical systems – focuses on the holistic

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lifecycle of materials. Although the circularity of materials has been studied in earlier centuries, the EMF showcased the framework as a practical approach to achieving several SDGs and ultimately combatting climate change (Reike et al., 2018:135-246; EMF, 2019:4-62).

A critical element in the CE framework from the EMF is the consumer and user aspects, which connect to the social pillar needed for a sustainable society (McDonough and Braungart, 2002:202). This framework is discussed in Section 2.4.1. A link between the SDGs and the CE has been developed by Garcia-Saravia Ortiz-de-Montellano et al. (2023:352-362) and can be summarised in Figure 10, showcasing what pathway is needed from the one to the other.

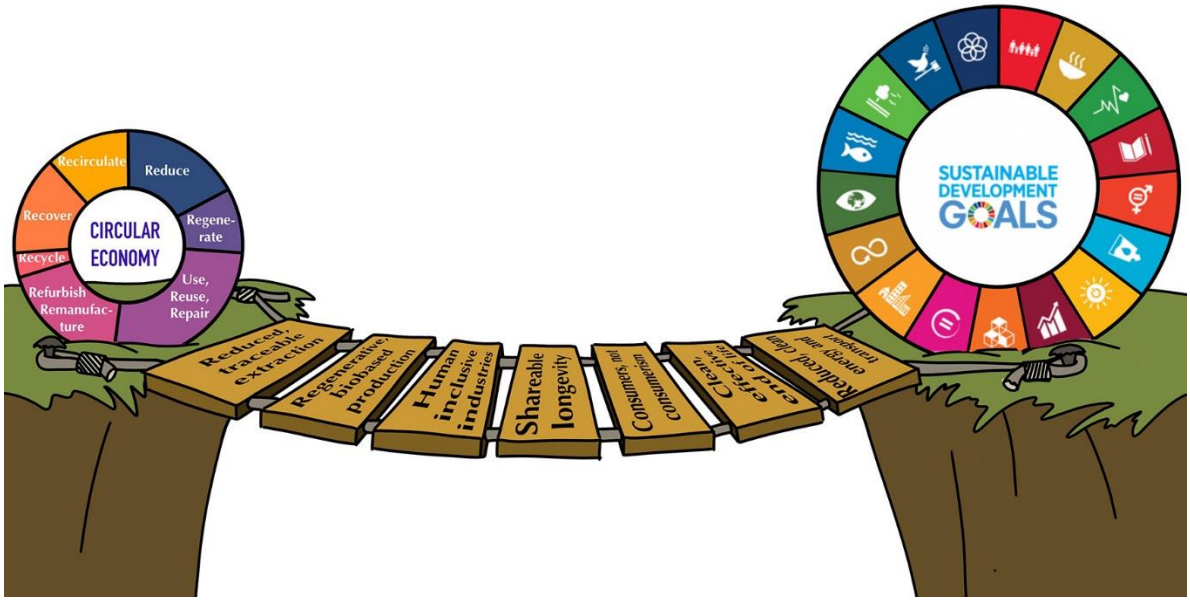

Figure 10. Circular economy supports pathways towards advancing Sustainable Development Goals (Garcia-Saravia Ortiz-de-Montellano et al., 2023:352-362).

The study of Garcia-Saravia Ortiz-de-Montellano et al. (2023:352-362) analysed 27 circularity strategies and their potential influence on the 17 SDGs and their 169 associated targets. The findings reveal that CE strategies can contribute to all SDGs, particularly SDGs 8, 12, and 13, while their impact is comparatively lower on SDGs 4, 5, 10, and 16. This impact is contingent on adherence to the seven identified pathways, as seen in Figure 11, such as regenerative production and inclusive industries. Pathways 2, 4, and 6 notably demonstrated the most significant influence, accounting for 66% of potential SDG contributions. That is also why this study aims to focus more on the social pillar and increase the other pathways from the CE towards the SDGs.

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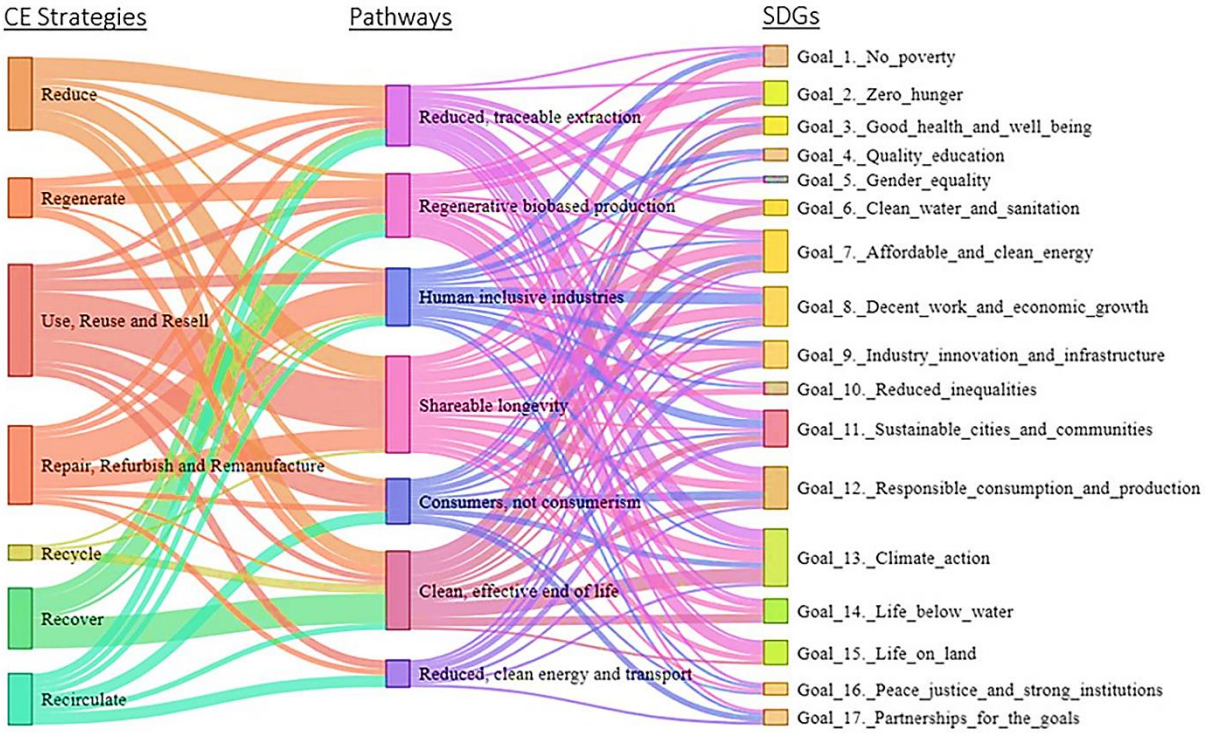

Figure 11. CE Practices to the SDGs through seven specific pathways. (Garcia-Saravia Ortiz-de-Montellano et al., 2023:352-362)

Another topic on the social pillar is the drive for corporations to focus on social objections rather than maximising profits, which is termed Corporate Social Responsibility (CSR) (Brin and Nehme, 2021:159-174).

CSR is the new “quality” driven topic in companies’ mission statements, and it is embedded in performance measurements, supply chains and core objectives of management (Hamed et al., 2022:2-13). Some authors critique CSR as a public relations utility for marketing products or other green-related functions, and others claim it gives companies a competitive advantage and enhances brand awareness (Grigore et al., 2021:763-782). Whether it is founded in moral responsibility or financial expansion, CSR is a critical change agent for sustainability, as indicated by Visser and Crane (2010:5-32)

The abovementioned topic of change agents is linked to SE through ST. Heiskanen et al. (2016:218-226), Redman and Wiek (2021:1-11) and (Robertson, 2021:140-146) studied the essential competencies of sustainability change agents. One of the main findings includes ST. Sustainability change agents must identify systems, evaluate interdependencies, and perform association analysis and integration. The following section discusses the different subject matter of SE, such as ST and SD.

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2.2.2. Background of Systems Engineering and Systems Thinking

Blanchard et al. (1990:846) explore several definitions for SE and ultimately settle on the preferred definition as: “An engineering field where a top-down approach is taken to see a system as a whole, where engineers are orientated towards observing the complete life cycle and identifying system requirements throughout all the phases”. The authors continue to define SE as a field that recognises the required collaborative efforts of several disciplines and the management of interfaces between them within systems development. A more detailed discussion of SE is given in Sections 2.3.2 and 2.4.2.

Senge (2006:389-400) describes ST as: “a discipline for seeing wholes. It is a framework for seeing interrelationships rather than things and patterns of change rather than static ‘snapshots’.” In Figure 12, the SE approach is explained with elements from ST to show how they are linked.

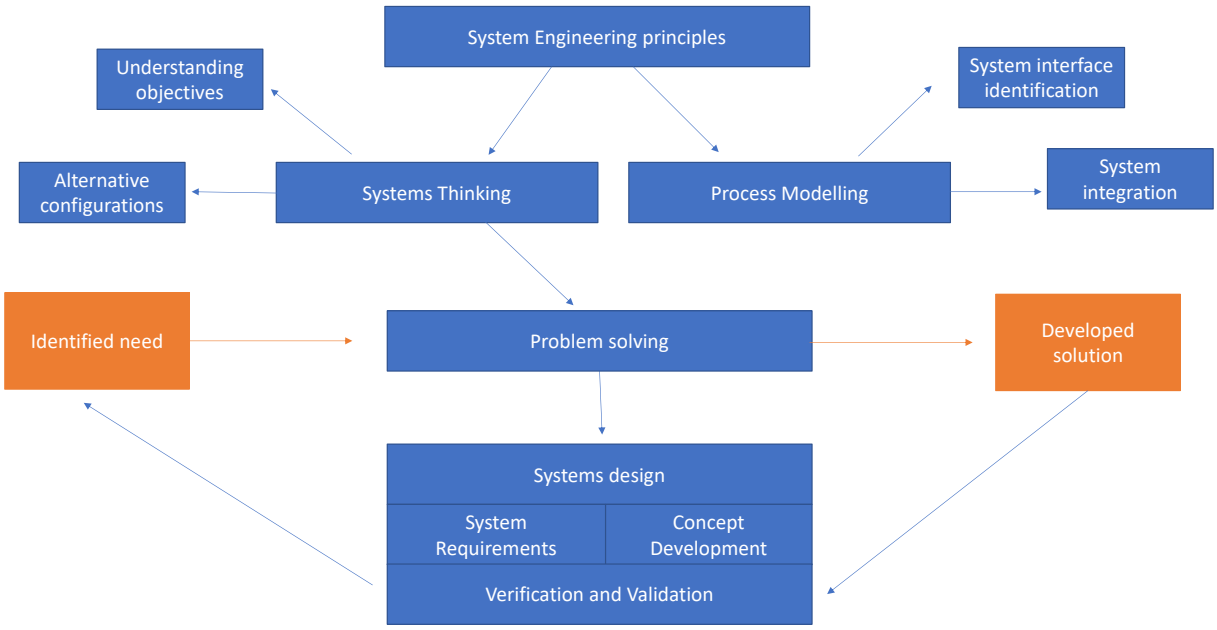

Figure 12. Systems Engineering principle dependencies – Adapted from Haberfellner et al. (2019:3-26)

ST includes an environment-oriented view, an effect and structure-oriented view, and simple input-output views, according to Haberfellner et al. (2019:3-26). It is argued that the ST view originated from the earlier versions of the Shewart cycle. This cycle, also called the PDCA structure, is illustrated in Figure 13. Later on, the cycle was also adapted to include ‘study’ rather than ‘check’ and was called the PDSA (Deming and Cahill, 2018). A more detailed discussion of ST is given in Sections 2.3.3 and 2.4.3.

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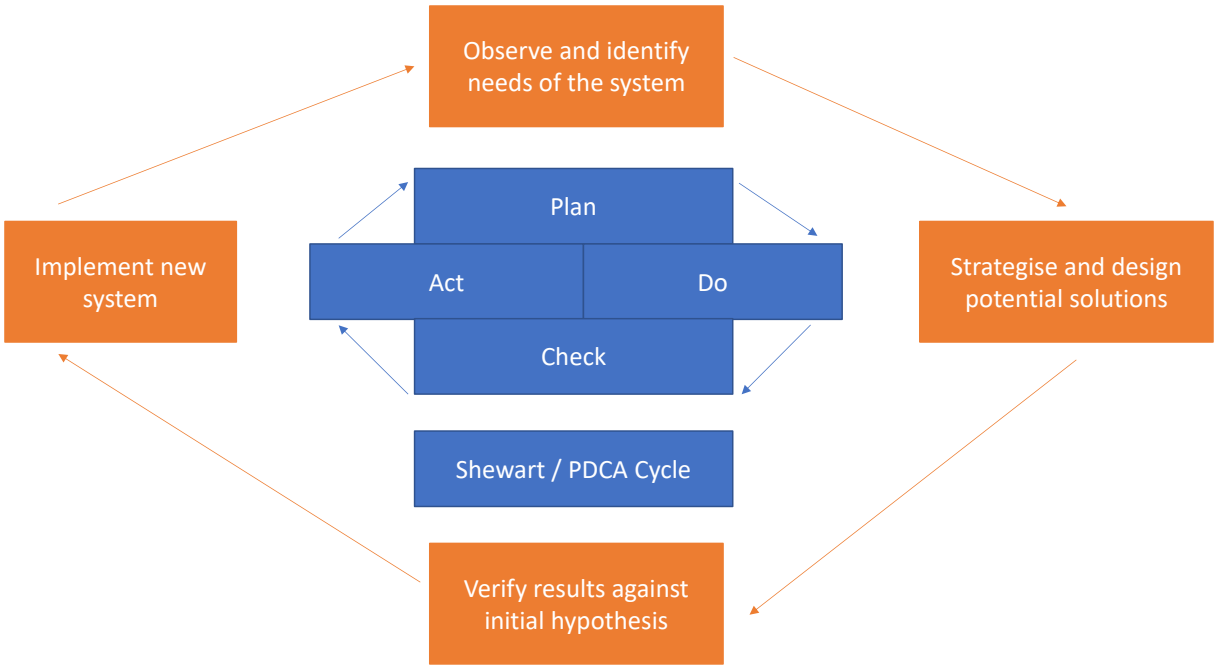

Figure 13. PDCA cycle illustrated with ST elements. Adapted from Deming (2000:247)

According to Figure 13, understanding the system before designing solutions is crucial. This thesis identifies several biases in the current sustainability systems to strategise ways to minimise negative biases. In the following section, an exploration of cognitive biases is given.

2.2.3. Background of Cognitive biases

Berthet (2022:1-13) studied the different impacts of individual cognitive biases on professional decision-making. The four occupations studied included finance, medicine, law, and management. The two conclusions made in the study are that almost a dozen cognitive biases significantly impact decision-making. Despite considerable debiasing focus, the primary cognitive bias was identified as overconfidence. The second finding supported by the study is that the impact of cognitive biases differs across the areas of finance, medicine, law, and management, studied by Berthet (2022:1-13). This is an important finding for this research, as different regions were identified to study the applicable cognitive biases. The different regions are internal and external stakeholders, as specified in Figure 1.

Two other topics that connect with cognitive biases are explored before more details about different biases are shared. The first topic is directionality. Directionality in STS is the notion of actors' tenet to become blind to choices when technical or social choices are the norm, respectively. Socio-technical change can only change direction if both disciplines are considered (Schot and Kanger, 2018:1045-1059).

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Environmental psychology is the second topic that connects with cognitive biases in this study. Much research is currently focused on how consumer behaviour plays a role in the external environment. Studies into how consumer preferences and consumption patterns influence the environment are also prevalent in journals (Qiu et al., 2020:3-6; Rondoni and Grasso, 2021:5-25; Sandberg, 2021:2-15; Lin and Yang, 2023:2-7). The need exists to understand how social influences on pro-environment behaviour can be managed (Gifford and Nilsson, 2014:141-157; Dragolea et al., 2023:1-18).

This brings back the topic of cognitive biases and their role in sustainability. It has been proven that biases, also known as 'mental shortcuts', can impact negatively or positively (Tversky and Kahneman, 1974:1124-31; Sharifi et al., 2024:1-15; Enke et al., 2023:818-832).

Several biases are listed in the following list, and discussions are held on how they can influence sustainability positively or negatively.

- **Confirmation bias**
  - Positive influence: Confirmation bias refers to the tendency to interpret new information as confirmation of your preexisting beliefs and opinions. If your belief is already positive or supports a good cause, this will positively enforce that belief (Michel and Peters, 2020:2757-2772).
  - Negative influence: Our minds reinforce our pre-existing ideas because being right helps preserve our sense of self-esteem, essential for feeling secure in the world and maintaining positive relationships (Ruzzier and Woo, 2023:379-390). Ruzzier and Woo also deliberate that people feel unintelligent when faced with alternate views and reject those views to keep their self-esteem.
  - Real-world examples: Confirmation bias is also incredibly pervasive online, particularly with social media. We tend to read online news articles that support our beliefs and fail to seek out sources that challenge them (Zhao et al., 2020). Various social media platforms, such as Facebook, help reinforce our confirmation bias by feeding us stories we are likely to agree with (Mao et al., 2021:816-827).
- **Hindsight Bias**
  - Positive influence: Hindsight bias refers to perceiving past events as more predictable than they were (Roese and Vohs, 2012:411-426). Cognitive and motivational explanations exist for why we feel more confident based on experience (Ackerman et al., 2020:731-744).
  - Negative influence: It is essential to do all we can to reduce this bias because when we are overly confident about our ability to predict outcomes, we might make future risky decisions that could have potentially dangerous outcomes

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(Ackerman et al., 2020:731-744).

- Real-world examples: In 1993, Dorothee Dietrich and Matthew Olsen asked college students to predict how the U.S. Senate would vote on the confirmation of Supreme Court nominee Clarence Thomas (Dietrich and Olson, 1993:377 - 378).
  Before the vote, 58% of participants predicted that he would be confirmed, but after his confirmation, 78% of students said that they thought he would be approved – a prime example of hindsight bias.

- **Self-Serving Bias**
  - Positive influence: Self-serving bias refers to the tendency to take personal responsibility for positive outcomes (Lammers and Burgmer, 2019:1087-1095).
  - Negative influence: We quickly take credit for positive outcomes and divert the blame to negative ones to boost and preserve our ego, which is necessary for confidence and healthy relationships with others (Zhang et al., 2018:236-244).
  - Real-world examples: Self-serving bias is prevalent in sports and the workplace. For example, athletes are quick to take responsibility for personal wins, attributing their successes to their hard work and mental toughness, but point to external factors, such as unfair calls or bad weather, when they lose (Allen et al., 2020:1027-1043).

- **Anchoring Bias**
  - Positive influence: Anchoring bias is closely related to the decision-making process and occurs when we rely on either pre-existing information or the first piece of information (the anchor) when making a decision. This can be positive when the initial belief is correct (Tversky and Kahneman, 1974:1124-1131).
  - Negative influence: One theory, known as anchoring and adjustment, argues that once an anchor is established, people insufficiently adjust away from it to arrive at their final answer, and so their final guess or decision is closer to the anchor than it otherwise would have been (Yasseri and Reher, 2022:1001-1021).
  - Real-World examples: For example, if you first see a T-shirt that costs R1,000 and then a second one that costs R100, you're more likely to see the second shirt as cheap as you would if the first shirt you saw was R120. Here, the price of the first shirt influences how you view the second. Another theory, selective accessibility, holds that although we assume that the anchor is not a suitable answer (or an appropriate price going back to the initial example) when we evaluate the second stimulus (or second shirt), we look for ways in which it is similar or different to the anchor (the price being way different), resulting in the anchoring effect (Mussweiler and Strack, 1999:135-167).

- **Availability Bias**
  - Positive influence: Information that comes to mind faster influences our decisions about the future. Just like hindsight bias, this bias is related to memory, which

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can be positive if the memory is principled (Fares, 2014:118). Instead of being a fabrication of memory, it is an overemphasis on a particular memory.

- Negative influence: In the workplace, if someone is being considered for a promotion but their boss recalls one bad thing that happened years ago but left a lasting impression, that one event might have an outsized influence on the final decision (Hayibor and Wasieleski, 2009:151-165).
- Real-World examples: A typical example that is used to demonstrate the availability heuristic describes how seeing several television shows or news reports about shark attacks (or anything that is sensationalised by the news, such as serial killers or plane crashes) might make you think that this incident is relatively common even though it is not at all. Regardless, this thinking might make you less inclined to go in the water the next time you go to the beach (Adams et al., 2020:17497).

- **Inattentional Blindness**
  - Positive influence: When a person fails to notice a stimulus in plain sight because their attention is directed elsewhere, it might be positive if their attention is toward something constructive (Kreitz et al., 2020:1055-1065).
  - Negative influence: When we focus a lot of our energy on one incentive, we are depleting our cognitive resources and unable to process additional stimuli concurrently (Mack, 2003:180-184).
  - Real-world examples: While driving a car, you might be so focused on the road ahead that you overlook entirely a car swerve into your traffic lane. Because your attention is directed elsewhere, you are not able to react in time, potentially leading to a car accident (Saryazdi et al., 2019)

In conclusion, exploring various cognitive biases has illuminated how these inherent mental shortcuts shape human perception, judgment, and decision-making. This analysis has demonstrated both the positive and negative impacts that cognitive biases can exert on individuals and their interactions within diverse contexts.

On the positive side, cognitive biases often serve as adaptive mechanisms that facilitate swift decision-making in everyday life. For instance, confirmation bias aids in filtering information, allowing individuals to quickly make sense of the vast amount of data they encounter. Additionally, the availability heuristic can help individuals make efficient choices by relying on readily available information, thus conserving cognitive resources. When harnessed effectively, these biases enable individuals to navigate complex environments with limited time and mental capacity.

However, the negative impacts of cognitive biases cannot be overlooked. Biases such as the anchoring effect can lead to flawed judgments and decision-making, fostering

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errors in forecasting and suboptimal choices. These biases may also contribute to misunderstandings and conflicts in interpersonal relationships, as perspectives become skewed by preconceived notions and limited information.

The study of cognitive biases underscores the complex interplay between human cognition and decision-making processes. While these biases can expedite choices and enhance adaptability, they can lead to errors and suboptimal outcomes. Individuals and organisations can cultivate more effective decision-making strategies by understanding and addressing cognitive biases, fostering better outcomes across various domains.

The Cognitive Bias Codex, shown in Figure 14, created by Buster Benson, is a powerful visual representation of the numerous cognitive biases that influence human thinking and decision-making. As our minds process information and make judgments, cognitive biases can often lead us astray, affecting our perception, memory, and reasoning abilities (Calero Valdez et al., 2018:13-27). The Cognitive Bias Codex is an insightful and accessible resource for navigating this complex landscape of biases.

By organising over 180 cognitive biases into a comprehensive infographic, the Codex offers a bird's-eye view of the complex web of mental shortcuts and prejudices that impact our daily lives. From confirmation bias and availability heuristics to anchoring and framing effects, the Codex categorises these biases into distinct clusters, providing a user-friendly reference for understanding their underlying mechanisms.

The Cognitive Bias Codex is a valuable tool for individuals seeking self-awareness and critical thinking, and it finds applications in fields such as psychology, sociology, economics, and decision science. Professionals in these domains can utilise the Codex to identify potential biases affecting research methodologies, policy-making, and problem-solving approaches.

This introduction explores the significance of the Cognitive Bias Codex, highlighting its role in illuminating the complexities of human cognition and the importance of recognising and mitigating biases for making more rational and well-informed choices. As the research delves deeper into the Codex, the research gains invaluable insights into how our minds interpret the world around us, empowering us to navigate cognitive biases more effectively in pursuit of truth and better decision-making.

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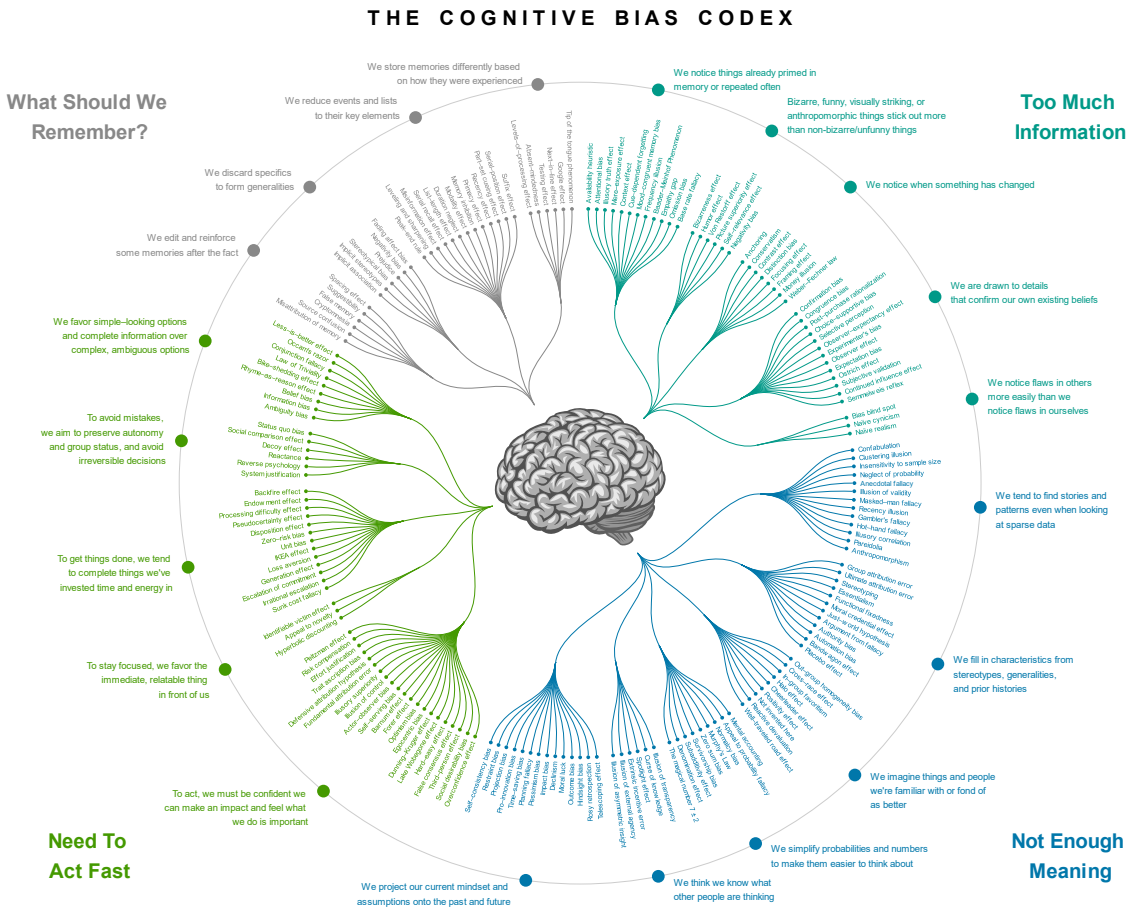

Figure 14. Cognitive bias codex (Ellis, 2018:1-10)

In conclusion, the comprehensive review of cognitive biases and their underlying mechanisms has unveiled a profound understanding of the intricate ways in which human cognition operates. The exploration of the historical background of cognitive biases has provided valuable insights into the evolution of research and the recognition of these mental shortcuts as integral components of human decision-making. Moreover, the elucidation of the cognitive bias codex has served as a comprehensive framework, categorising and explicating the multitude of biases that shape our perceptions and judgments. This literature review not only underscores the pervasive nature of cognitive biases across various domains but also emphasises the need to acknowledge and address these biases to enhance the accuracy and quality of decision-making processes in individual and collective contexts.

2.2.4. Background of Design Science Research

DSR is discussed as part of the literature review because it provides this study's theoretical foundation and methodological framework. By including DSR in the literature review, the research aligns with established approaches to problem-solving in complex, real-world systems, such as the CE. The discussion of DSR helps establish

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how the models in this thesis are developed iteratively, from problem identification (awareness) to solution (artefact) creation, validation, and refinement. This ensures that the research is both scientifically thorough and practically applicable.

DSR is a methodology that seeks to create and evaluate artefacts designed to solve identified problems (Johannesson and Perjons, 2021:77-93). In the context of CE and cognitive biases, DSR provides a structured approach to developing strategies and tools that leverage biases and support CE adoption (Peffers et al., 2006).

The DSR process typically involves the following steps (Hevner et al., 2024:1-10; Schoormann et al., 2023:307-325):

- Problem identification and motivation: Clearly define the problem (cognitive biases hindering CE adoption) and articulate the importance of solving it.
- Objectives of a solution: Determining the research goals (e.g., creating a conceptual model to leverage cognitive biases).
- Design and development: Creating the artefact (e.g., strategies, tools, models) to address the problem.
- Demonstration: Demonstrating the artefact in a relevant context to show its utility.
- Evaluation: Evaluate the artefact to assess its effectiveness.
- Communication: Sharing the findings with relevant stakeholders.

DSR closes the gap between theory and practice by emphasising the development of innovative solutions and their practical applications. The iterative approach involves problem identification, solution design, evaluation, refinement, and further testing. This cycle ensures that the artefacts are theoretically sound and practical in real-world scenarios. DSR is distinct in its focus on creating artefacts, including models, methods, constructs, and instantiations designed to improve existing systems or address new challenges. By integrating research methods with creative design processes, DSR contributes to academic knowledge and practical advancements (Arnott and Pervan, 2012:923-949).

The background of DSR is deeply rooted in the philosophy of pragmatism, which values practical solutions and real-world applicability. It emerged as a response to the limitations of traditional research methods that often prioritise theoretical contributions over practical relevance. DSR integrates elements from various disciplines, including information systems, management science, and software engineering, to develop innovative and implementable solutions. Several other disciplines also influenced DSR (Hunziker and Blankenagel, 2024:97-116). Fundamental principles of DSR include problem relevance, design as a search process, and the necessity of evaluation. Researchers employing DSR must navigate the dual imperatives of creating valuable and theoretically significant artefacts. This dual focus ensures that the research advances academic understanding and provides tangible benefits to practitioners and

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stakeholders (March and Smith, 1995:251-266; Hunziker and Blankenagel, 2024:97-116; Oosthuizen, 2014; Scribante, 2019).

2.3. Current Theories

In today's rapidly changing world, pursuing sustainable practices and CE models has gained significant attention across various disciplines (Piccarozzi et al., 2022). This passage thoroughly explores the current theories and literature around essential concepts such as sustainability, CE, SE, ST, SD, cognitive biases, and decision-making. By delving into these interconnected areas, this section aims to understand how they shape our understanding of complex problems and influence decision-making processes, as discussed in Chapter 1. By exploring the latest research and theories, this research uncovers the potential interactions and challenges when addressing global issues from an integrated and holistic perspective. As this study delves into this diverse knowledge landscape, valuable insights are gained into fostering a more sustainable and resilient future.

Table 3 presents a more comprehensive bibliometric analysis that sheds light on the most influential articles on Sustainability, CE, SE, ST, SD, Cognitive biases, and Decision-making. Leveraging the vast repository of scholarly knowledge available on the Web of Science, this analysis explores the citations garnered by critical articles on each topic, providing valuable insights into the most impactful research in these fields. By quantitatively assessing the citation counts, this study identifies the seminal works that have significantly shaped and advanced the understanding of sustainability, CE, and various interconnected systems-related disciplines. As the research delves into the results presented in the accompanying table, the intellectual milestones that have guided scholarly discourse are uncovered, providing a roadmap for further exploration and innovation in these critical areas of study.

Using the Web of Science database to search for keywords as topics and filtering for the highest citation papers is an effective strategy for identifying influential research in a specific field (Singh et al., 2021:5113-5142; Birkle et al., 2020:363-376). This approach involves entering relevant keywords into the search bar and selecting "Topic" to ensure the search encompasses titles, abstracts, and keywords. Once the results are generated, applying a filter to sort by the number of citations allows researchers to identify the most impactful studies quickly. High citation counts indicate that other researchers have widely recognised and referenced the paper, signifying its importance and influence in the field. This method helps gather seminal works and provides a comprehensive overview of the key developments and current trends in the research area. By focusing on highly cited papers, researchers can build on a solid foundation of established knowledge and ensure their work is aligned with leading research.

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Table 3. Systematic literature review of research keywords when writing the thesis 2024/06.

Topic	Title of the article and journal	Number of citations	Source
Sustainability	Planetary boundaries: Guiding human development on a changing planet; Science Journal	6764	(Steffen et al., 2015:11)
Circular Economy	The Circular Economy: A New Sustainability Paradigm?; Journal of Cleaner Production	3167	(Geissdoerfer et al., 2017:757-768)
Systems Engineering	Design Techniques and Applications of Cyberphysical Systems: A Survey; IEEE Systems Journal	476	(Khaitan and McCalley, 2015:350-365)
Systems Thinking	Wicked Problems: Implications for Public Policy and Management; Administration & Society Journal	865	(Head and Alford, 2015:711-739)
Systems Dynamics	Universal resilience patterns in complex networks; NATURE	727	(Gao et al., 2016:307-312)
Cognitive biases	Explanation in artificial intelligence: Insights from the social sciences; Artificial Intelligence Journal	1848	(Miller, 2019:1-38)
Sustainable decision-making	Towards sustainable development through the circular economy review and critical assessment of current circularity metrics; Resources Conservation And Recycling	393	(Corona et al., 2019)
Design Science Research	FEDS: a Framework for Evaluation in Design Science Research; European Journal Of Information Systems	363	(Venable et al., 2016:77-89)

2.3.1. Importance of Sustainability

The idea that the Earth is limitless has been disproven many times over, indicating that there are many boundaries. Humanity has already been getting to some of these boundaries or limits. Sustainability is essential for maintaining the resilience of the Earth system as a whole (Chapin et al., 2022:1907-1920). One decision can proliferate inside a system, influencing several outcomes. This is called the butterfly effect. McDonough et al. (2013:213) describe this Butterfly effect in their book The Upcycle: Beyond Sustainability--Designing for Abundance as Chaos Theory. When people realise how their small actions can echo through other systems either positively or negatively, when it comes to sustainability, the need is there for the butterfly effect to ripple the knowledge and processes out across all industries.

2.3.2. Why Systems Engineering is Useful

The interdisciplinary nature of SE lends itself to realising a socio-technical approach. The top-down approach to view the system as a whole, the life-cycle orientation to address all the phases in the system, and the definition of the system requirements are all crucial to finding better solutions to sustainability endeavours. Blanchard et al.

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(1990:846) and Reynolds and Holwell (2020:1-24) explain in detail that SE is a new thought process to manage systems in a synergetic manner. This method will give essential insight into how sustainability systems can be better understood.

2.3.3. Systems Thinking Approaches

ST is an essential principle of SE. This systems approach is the observation of how the parts of the system should perform to enable the highest function of the system. This section looks at the importance of ST at the early stages of the life cycle of a system. Investing in ST at the problem definition stage is crucial to obtain all the potential benefits from properly implemented system solutions.

Several different ST cycles have been reinvented through the years (Cabrera et al., 2023:1-51). Previously, the Shewart cycle was illustrated, which is but one of these ST approaches. Others include the approaches defined by Senge (2006:389-400) and Covey (1991:219) in their widely popular books called “The Fifth Discipline” and “The 7 Habits of Highly Effective People”, respectively. When first published, Bahill and Gissing (1998:516-527) took all these approaches and evaluated their similarities. The SIMILAR approach was developed and will be applied in this research, as shown in Figure 15. The SIMILAR approach stemmed from several ST approaches but is positioned under SE approaches. Several process modellers also used this approach (Bahill and Madni, 2023:195-256; Imtiaz, 2023:21-49; Schismenos et al., 2022:594-608). The SIMILAR acronym is State, Investigate, Model, Integrate, Launch, Assess, and Re-evaluate.

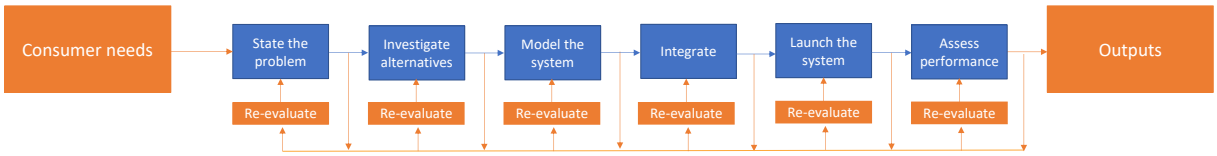

Figure 15. A SIMILAR Approach was implemented in this research. Adapted from Bahill and Gissing (1998:516-527)

2.3.4. System Dynamics Approaches

SD considers process modelling to be another essential principle of SE. SD is an interdisciplinary approach that aims to understand the behaviour of complex systems over time. It has proven a powerful tool for modelling and analysing dynamic systems, offering insights into the interactions and feedback loops that shape their behaviour (García, 2023:11-248; Eidin et al., 2024:1-28). Several influential topics within the SD framework have emerged, significantly contributing to its application across various domains:

- Feedback loops and causal relationships: Central to SD is understanding feedback loops and causal relationships within a system. This topic explores how various

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elements in a system interact with each other, creating dynamic patterns of behaviour. By identifying reinforcing and balancing loops, researchers can grasp the potential for amplifying or stabilising effects, making it a crucial aspect in understanding system behaviour (Sterman, 2000:982)

- System archetypes: System archetypes are recurring patterns of behaviour found in complex systems. These archetypes, such as "Tragedy of the Commons" or "Shifting the Burden," provide generic structures that can help recognise common systemic challenges and design appropriate interventions (Senge, 2006:389-400; Hardin, 1968:1243-1248)
- Modelling and simulation: Developing comprehensive models is essential in SD. This topic delves into the techniques and methodologies for constructing dynamic models that capture the underlying complexities of the system under study. Simulation of these models enables researchers to test scenarios, anticipate system responses, and evaluate potential interventions (Forrester, 1961:464)
- Policy design and decision-making: SD supports examining policy options and decision-making in complex systems. By simulating different policy interventions, decision-makers can identify potential unintended consequences and assess the long-term impacts of their choices (Richardson, 2011:219-243)

Back to sustainability, SD can be pivotal in addressing complex sustainability challenges. For instance, it has been applied to study the dynamics of ecological systems, the impact of climate change, resource management, and urban development (Struben and Sterman, 2008:1070-1097; Guemouria et al., 2023:1-27; Barati et al., 2023:2-6; Li et al., 2023:3-8). By understanding the interconnectedness of ecological, social, and economic factors, SD aids in crafting sustainable policies and strategies that account for long-term consequences and the need for resilient solutions (Vennix, 1999:379-401). Moreover, when dealing with wicked problems like sustainability issues, SD provides a structured approach to navigate uncertainties and complexities, facilitating better decision-making for a sustainable future. By applying SD to sustainability, researchers and policymakers can gain valuable insights into the complex relationships between human activities and the environment, leading to more informed and effective measures for sustainable development.

2.3.5. Influences of Cognitive Biases on Decision-making

In the realm of decision-making, cognitive biases exert a powerful influence on human judgment and can significantly impact choices related to sustainability. Cognitive biases are systematic errors in thinking that arise from the brain's attempt to simplify information processing. These biases can lead individuals and policymakers to make suboptimal decisions, hindering progress towards sustainable practices. Recognising and addressing these biases is essential to foster effective, sustainable decision-making.

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One prominent cognitive bias relevant to sustainability is the "status quo bias". This bias causes individuals to prefer maintaining the current situation rather than opting for change, even if the change may lead to better environmental outcomes. For instance, when presented with the option to transition to renewable energy sources, individuals may stick to traditional fossil fuels due to familiarity and comfort with the existing energy infrastructure (Samuelson and Zeckhauser, 1988:7-59; Gârdan et al., 2023:676; Aimone, 2024:1-25).

Another cognitive bias impacting sustainable decision-making is the "optimism bias". This bias makes people overly optimistic about the future, underestimating potential risks and challenges associated with environmental issues. In the context of sustainability, this bias may lead to neglecting the long-term consequences of resource depletion or climate change, delaying necessary actions for mitigation and adaptation (Sharot, 2011:941-945).

Moreover, the "confirmation bias" can significantly influence how information related to sustainability is perceived and acted upon. This bias drives individuals to seek and favour information that aligns with their pre-existing beliefs, reinforcing their existing perspectives and ignoring contradictory evidence. As a result, decision-makers may overlook crucial scientific findings or dismiss alternative sustainable solutions, hindering progress in addressing environmental challenges (Nickerson, 1998:175-220; Elmor et al., 2024:1-26; Halawa, 2024:1-14).

To illustrate, consider a scenario where policymakers debate implementing a carbon tax to reduce greenhouse gas emissions and combat climate change. The confirmation bias could lead some policymakers only to consider evidence supporting their belief that the tax would negatively impact the economy while disregarding studies highlighting the potential benefits of carbon pricing on reducing emissions and driving investments in green technologies.

Addressing cognitive biases in sustainability decision-making requires conscious effort and applying critical thinking. Encouraging diverse perspectives, promoting open dialogue, and providing decision-makers with unbiased data and research are essential strategies to leverage the influence of cognitive biases. By recognising and challenging these biases, policymakers and individuals can make more informed and sustainable decisions, fostering positive change for the environment and future generations.

The concepts discussed in the previous paragraphs about cognitive biases and their influence on decision-making can be further explored and understood through the lens of Malcolm Gladwell's book, "Blink: The Power of Thinking Without Thinking." Gladwell delves into intuitive decision-making in this best-selling book, showcasing how our

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minds often make split-second judgments based on limited information and experience (Gladwell, 2005:277).

The cognitive biases highlighted previously, such as the status quo bias, optimism bias, and confirmation bias, align with Gladwell's exploration of rapid cognition, which refers to the unconscious thought processes that shape our decisions in the blink of an eye. He argues that these seemingly automatic judgments can be influenced by various factors, including biases and prejudices ingrained in our minds.

Gladwell's "Blink" provides real-life examples and case studies demonstrating how cognitive biases can lead to successful intuitive decisions and disastrous errors. For instance, he examines cases in which experts' quick, intuitive assessments have resulted in accurate outcomes and contrasts them with situations where snap judgments have led to grave consequences, particularly when biases cloud judgment.

In sustainability decision-making, the insights from "Blink" shed light on how cognitive biases can affect policymakers and individuals alike. By understanding the subconscious influences that drive decision-making processes, people can better recognise and address cognitive biases that may hinder progress towards sustainable practices. The book also emphasises the importance of deliberately cultivating an open and diverse decision-making environment, where quick judgments are informed by evidence-based reasoning and biases are identified and challenged.

Ultimately, Gladwell's exploration of intuitive decision-making in "Blink" offers a valuable perspective on how cognitive biases can impact our approach to sustainability. By incorporating insights from this work into understanding cognitive biases and decision-making, people can foster more informed and mindful choices that align with sustainable goals and contribute to a more environmentally conscious future.

2.3.6. Identification of Representative Cognitive Biases

Numerous researchers have explored and identified representative cognitive biases in various studies, shedding light on the pervasive nature of these biases and their impact on decision-making processes. For instance, Tversky and Kahneman (1974:1124-1131) conducted seminal research on the availability heuristic, demonstrating how individuals rely on readily available information when making judgments, even if that information is not representative of the overall data. Their work has been foundational in understanding how biases can lead to suboptimal choices and influence perceptions of risk and uncertainty.

Similarly, researchers such as Slovic et al. (2007:1333-1352) have explored the affect heuristic, revealing how people's emotional responses to a particular issue can strongly influence their judgments and decisions. This emotional bias can sway sustainability-

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related choices, where emotionally charged environmental issues may receive disproportionate attention or resource allocation, regardless of their significance in the broader context of sustainability challenges.

Furthermore, the framing effect, studied by Levin et al. (1998:149-188), demonstrates how the presentation of information can significantly influence decision-making. When sustainability issues regarding potential losses or gains are framed, individuals' risk preferences may shift, impacting their willingness to engage in sustainable practices or support environmentally friendly policies.

Linking back to sustainability, identifying representative cognitive biases is crucial for understanding how these biases may hinder progress towards sustainable practices and policies. Biases such as the status quo bias could impede the adoption of sustainable technologies or lifestyle changes, as people may be reluctant to deviate from familiar routines or existing infrastructure. The optimism bias might lead to underestimating the severity of environmental challenges, delaying urgent action or investment in sustainable solutions. Moreover, the confirmation bias could hinder cooperation and collective efforts to address sustainability issues.

Recognising and addressing cognitive biases in the context of sustainability is essential to fostering informed decision-making. Researchers, policymakers, and individuals must strive to overcome these biases and cultivate a culture of critical thinking, evidence-based reasoning, and open dialogue. By integrating insights from the study of cognitive biases into sustainability initiatives, people can ensure more effective strategies and policies that align with long-term environmental goals, promote resilience, and contribute to a sustainable future for future generations.

As this research explores cognitive biases in sustainability, the aim is to identify and understand how these biases influence participants' attitudes, behaviours, and decision-making related to sustainability issues. To achieve this goal, the research will design a comprehensive survey that delves into various cognitive biases that impact human thinking, as seen in Chapter 6. The survey will focus on the following cognitive biases: Confirmation Bias, Hindsight Bias, Self-Serving Bias, Anchoring Bias, Availability Bias, and Inattentional Blindness, as mentioned in 2.2.3.

Including the research method and questionnaire design in the literature review chapter serves several important purposes within this thesis. First, it provides a necessary contextual foundation by linking the chosen methodology with established research practices, ensuring that the approach is grounded in relevant theoretical frameworks. This connection helps to demonstrate that the research method is informed by previous studies and not developed in isolation. Second, it justifies the research approach, highlighting how the chosen method addresses gaps or limitations

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identified in the literature. The study gains transparency and rigour by embedding the research method and questionnaire design discussion within the literature review, illustrating that the tools used to collect data are rooted in proven methodologies. Finally, this integration facilitates a clear link between theory and practice, showing how the theoretical insights gathered from the literature are operationalised through the research design. In doing so, the literature review not only positions the study within the broader academic discourse but also enhances the coherence and credibility of the research process.

The biases, together with the research methods applicable to them, are discussed below:

- Confirmation bias: To address confirmation bias, the survey questions are drafted to present participants with balanced information about sustainability topics. The research will assess whether participants selectively focus on information that aligns with their beliefs while dismissing contradictory evidence.
- Hindsight bias: Retrospective questions are included that prompt participants to recall their past attitudes or behaviours concerning sustainability to investigate hindsight bias. By comparing participants' past beliefs with their current responses, the research can determine if hindsight bias leads them to perceive their past attitudes as more aligned with present sustainability efforts than they were at the time.
- Self-serving bias: Incorporated into the research are questions about participants' sustainability-related actions or contributions to explore self-serving bias. Through the analysis, the researcher assesses whether participants tend to take credit for positive, sustainable behaviours while attributing negative environmental impacts to external factors.
- Anchoring bias: To uncover anchoring bias, questions are included that present participants with different numerical values or metrics related to sustainability. By examining their subsequent responses, the researcher can observe whether the initial information provided influences their answers, indicating the presence of an anchoring effect.
- Availability bias: To identify availability bias, questions are designed that ask participants to recall specific sustainability-related events, examples, or instances. Through analysis, the research evaluates whether participants' responses are disproportionately influenced by easily retrievable or recent information, leading to an overrepresentation of certain factors.
- Inattentional blindness: To explore inattentional blindness, a scenario or text is included in which participants are focused on a primary sustainability task. Afterwards, the researcher inquired whether participants noticed any unexpected or significant details in the scenario that they may have missed while concentrating on the primary task.

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The inclusion of a discussion on qualitative and quantitative question formats within the literature review is motivated by the need to align the research methodology with established best practices in studying cognitive biases.

Qualitative and quantitative question formats, such as multiple-choice, ranking, and open-ended responses, are included throughout the survey to understand participants' cognitive biases comprehensively (Kuckartz and Rädiker, 2019:219-229; Aravindh and Thirupathi, 2019). Data analysis will involve descriptive statistics and thematic analysis to discern patterns and insights into the prevalence and impact of cognitive biases on sustainability-related attitudes and behaviours (Marcos-Merino et al., 2020:7445).

By presenting this methodological framework in the literature review, the study underscores the theoretical basis for selecting these question formats, demonstrating that the research design is grounded in previous successful approaches.

By executing this detailed action plan, the research aims to contribute to a deeper understanding of cognitive biases in sustainability, paving the way for more targeted interventions and strategies to promote rational and informed decision-making for a sustainable future. This creates a seamless link between the existing body of knowledge and the methodological choices made in the research, justifying their inclusion.

2.4. Current Models

To address complex sustainability challenges, researchers and practitioners have turned to diverse models and methodologies that offer valuable insights into the interconnected web of environmental, social, and economic factors (Ahmad et al., 2024:2965-2987; Wan et al., 2023:65-75; Al-Emran, 2023:2-5). These models provide systematic frameworks for analysing and understanding sustainability issues and decision-making processes. This exploration will explore some prominent models that have emerged as essential tools for researching sustainability and decision-making.

A model typically represents a simplified version of reality that is used to explain, predict, or simulate a specific phenomenon. Models often use variables and relationships between them to mirror complex systems in a structured way. For example, Sterman (2000:982) defines a model in the context of SD as a tool used to understand the behaviour of systems over time, helping to simulate potential outcomes and test different scenarios (Korteling et al., 2023:1-14). Similarly, Van der Vorst (2000:305) highlights that models serve to simplify real-world processes, allowing researchers to focus on critical variables and relationships that affect the system under study.

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On the other hand, a framework is broader and serves as a conceptual structure used to guide the development or analysis of models. A framework typically outlines the components and their relationships, providing a high-level structure for organising knowledge and theories. For instance, Miles and Huberman (1994:338) describe frameworks as tools that systematically integrate theories and concepts, guiding understanding how various elements interact within a particular domain. Similarly, Osterwalder and Pigneur (2010:278) use the term "framework" to describe a set of predefined elements and relationships that offer a comprehensive view of a business or scientific area.

In summary, a model focuses on representing specific elements of a system to simulate or predict behaviours. A framework is a conceptual guide that organises and structures models and their components.

2.4.1. The Circular Economy Model

Discussing the highest-profile global proponent of the CE is an excellent place to begin. The Ellen Macarthur Foundation (EMF or the Foundation) was initiated in 2009 by Ellen Macarthur, a British competitive ocean sailor (Stahel, 2016:435-438). The EMF has constructed a comprehensive CE framework, encompassing biological and technical systems as critical stakeholders. This study emphasises incorporating a human and social dimension into the system, involving users, enablers, and support structures.

The foundation of the CE framework rests upon three fundamental principles. Firstly, it centres around the responsible management of finite natural resources, focusing on their preservation and the transition to renewable alternatives. Secondly, it seeks to optimise resource utilisation by promoting circular flows, material sharing, and regeneration to achieve optimal efficiency. Lastly, the framework is geared towards enhancing system effectiveness by redesigning processes and eliminating the use of non-renewable and non-reusable materials.

A visual representation in Figure 16 illustrates the interplay between the technical and biological components:

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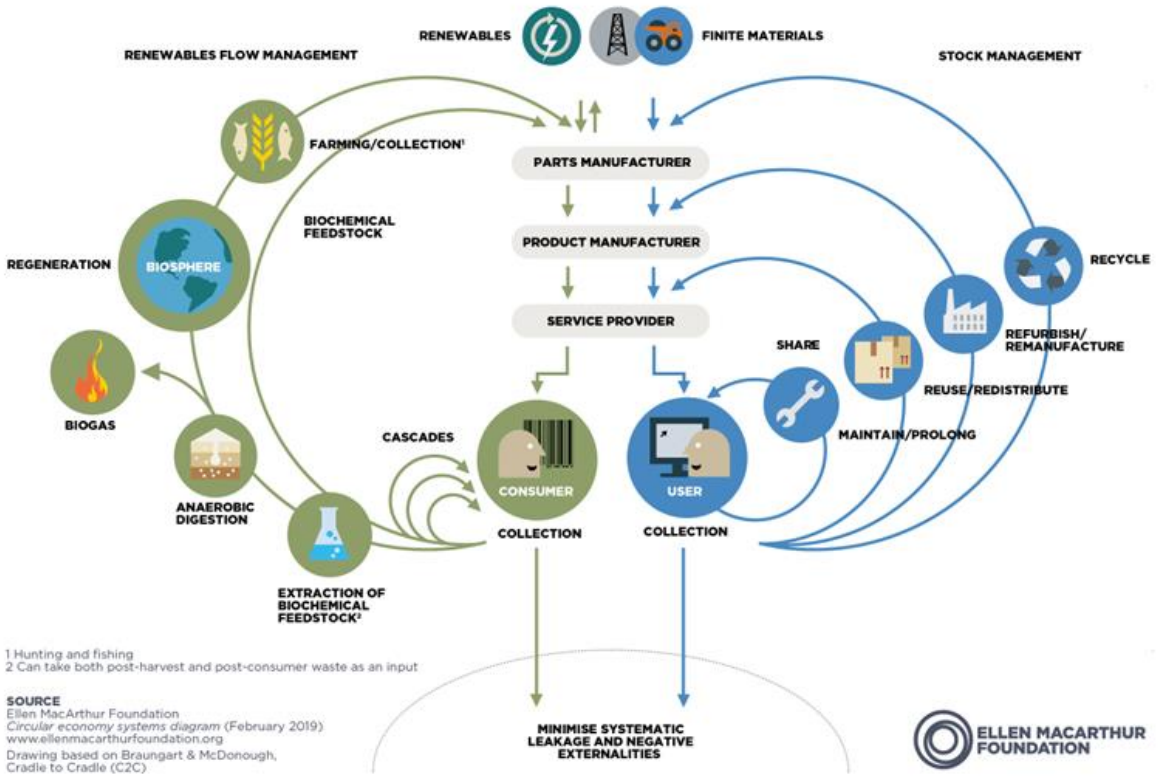

Figure 16. Technical and biological cycles for the CE as per McDonough and Braungart (2002:202); EMF (2019:4-62)

There are many different perspectives and definitions of what the CE entails in academic as well as public discourse. In particular, there is a divide between those who see CE as an opportunity to keep up current production and consumption patterns and those who highlight the need for decreased consumption or even post-growth (Barrie et al., 2022:106-208). The CE model has gained significant attention as a promising approach to fostering sustainability and resource efficiency. This model advocates a shift from the traditional linear "take, make, dispose" approach to a regenerative system where resources are continuously reused, recycled, and restored. By examining material flows, product life cycles, and waste management, the CE model offers a holistic perspective that seeks to minimise waste, promote sustainability, and create economic opportunities (Kirchherr et al., 2017:221-232).

Another sustainable model used by economists is the Doughnut Economy model. The Doughnut Economics concept challenges the entrenched perspective that Gross Domestic Product (GDP) is the sole indicator of economic progress. Instead, it presents an alternative vision of a globally oriented economic objective defined by a balanced boundary. The notion of boundless growth is discredited, highlighting that the prevalent economic yardstick worldwide is founded upon the unsustainable nature of unchecked expansion.

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In her work, Raworth (2017:216-222), an economist, explores the prevalent belief in the existing economic paradigm that champions perpetual economic growth, as shown in Figure 17. This belief, however, clashes with the finite limits of environmental resources and inevitably impacts humanity's well-being. The subsequent economic model aligns itself with the principles of the Doughnut Economy, emphasising the pursuit of a prosperous economy anchored in a robust social foundation.

Figure 17. Doughnut Economy model from Krauss (2018:452-457)

The Doughnut model emphasises the need to balance social foundations (such as equality, health, and education) with ecological ceilings (such as climate stability and biodiversity). This approach complements the exploration of cognitive biases in decision-making within the CE in this thesis by highlighting the necessity for sustainable development that avoids ecological overshoot while ensuring social equity. As stakeholders navigate the complexities of decision-making in the CE, the Doughnut framework serves as a valuable reference for ensuring that cognitive biases, whether supportive or obstructive, are examined in light of their broader impacts on human well-being and planetary boundaries. Integrating this model enriches the research by providing a visual and conceptual tool to guide sustainable decision-making, offering a clear benchmark for assessing how decisions align with long-term ecological and social sustainability goals.

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2.4.2. Soft Systems Methodology

In the literature review, it is essential to differentiate between the role of methodologies and theories. SSM is introduced here under current models because it provides a practical framework for addressing complex, real-world problems, much like the challenge of sustainable decision-making within the CE. SSM is widely applied to understand and model "wicked problems" that do not have straightforward solutions, making it a valuable tool for structuring the messy, human-centric issues encountered in the CE.

However, ST is more conceptual, focusing on understanding feedback loops, system archetypes, and interrelationships within the CE. While both SSM and ST aim to deal with complexity, they approach it from different angles. Therefore, SSM is discussed alongside other current models to highlight its practical utility in dealing with unstructured problems. At the same time, ST is reserved for discussing current theories in Section 2.3 to frame how mental models, feedback loops, and archetypes inform decision-making processes.

By positioning SSM here, the role is identified as a methodological tool that informs model building and stakeholder analysis, making it a complementary approach to the more theoretical lens of ST explored later. The distinction allows for a clearer motivation of the research methodology, ensuring that both the practical and conceptual aspects of dealing with complexity in sustainable decision-making are adequately addressed.

SSM is a qualitative systems-based approach that enables researchers to tackle ill-structured, messy, and complex problems like sustainability issues. Rooted in a human-centred perspective, SSM emphasises understanding social systems and stakeholders' diverse perspectives. Using rich pictures, conceptual models, and boundary judgments, SSM facilitates the exploration of multiple viewpoints, promoting learning and enhancing decision-making in complex socio-ecological contexts (Checkland and Poulter, 2006:200).

The application of SMM to this study is depicted in Figure 48 in another section. Johannes Watkins made significant contributions to the SSM field, building upon Peter Checkland's work (Watkins, 2000:266). He emphasised the social aspects of SSM, highlighting the importance of understanding and accommodating the diverse perspectives of stakeholders when addressing complex and ill-structured problems. Watkins stresses the role of rich pictures, which capture stakeholders' mental models and facilitate open dialogue and learning within problem situations. His work focused on using SSM as a practical approach to tackle real-world challenges, emphasising the importance of combining systems thinking with the human element to improve

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decision-making and promote sustainable solutions in complex socio-ecological contexts.

SSM and DSR are approaches to address complex, real-world problems but operate through different paradigms and focus areas. However, they can be linked and complementary when combined to tackle multifaceted issues. The link between SSM and DSR lies in their complementary strengths. SSM can be used in the initial stages of a study to explore the problem space, understand stakeholder perspectives, and identify critical issues and requirements. This groundwork is crucial for informing the design phase in DSR, where concrete solutions (artefacts) are developed. Using SSM to understand the context and nuances of the problem thoroughly, researchers can ensure that the artefacts designed in the DSR phase are relevant, practical, and aligned with stakeholder needs.

Furthermore, the iterative nature of both methodologies allows for a cyclical refinement process. Insights gained from evaluating DSR artefacts can feed back into SSM processes to further refine the understanding of the problem and the effectiveness of interventions. This interaction enhances the robustness and relevance of the problem understanding and the solutions developed.

SSM, emphasising exploring different perspectives and defining problems through conceptual models, can help identify the underlying structures and feedback loops that give rise to system archetypes. By using SSM, researchers can uncover the root causes of systemic issues and recognise archetypal patterns such as "Limits to Growth," "Shifting the Burden," or "Fixes that Fail." Understanding these patterns allows stakeholders to grasp better the system's dynamics and the potential unintended consequences of interventions.

Once these archetypes are identified and understood through SSM, DSR can be employed to design and implement artefacts that address the specific issues revealed by the archetypal analysis. For instance, if SSM reveals a "Shifting the Burden" archetype, where short-term fixes detract from long-term solutions, DSR can create artefacts focusing on sustainable, long-term solutions. These artefacts could be new processes, tools, or systems designed to break the cycle of short-term fixes and promote more sustainable practices.

System archetypes provide a framework for understanding the dynamic behaviours in complex systems, while SSM offers a methodology for exploring and defining these complexities in detail. DSR, in turn, builds on this understanding to create and test solutions. By integrating these approaches, researchers and practitioners can develop a comprehensive strategy for identifying, understanding, and addressing systemic problems. This integration ensures that solutions are theoretically robust, practically

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effective, and sustainable in addressing the recurring patterns identified through system archetypes.

2.4.3. System Archetypes

System archetypes represent the fundamental visualisation of complex ST and highlight the benefits of systemic solutions for complex issues while outlining the drawbacks of non-systemic approaches (Wolstenholme, 2004:341-356). These archetypes encapsulate complex models or systems in a simplified conceptual form. Several fundamental archetypes are outlined by Braun (2002:1-26) and discussed as follows.

- Fixes that fail: Employing reductionist reasoning often leads to solutions that merely address symptoms of complex problems. These "quick fixes" result in unintended complications, failing to resolve the root cause and leading to gradual deterioration.
- Shifting the burden: Concentrating on short-term remedies, like symptom alleviation, can lead to unanticipated side effects that hinder the implementation of essential solutions. This archetype underscores the misguided emphasis on temporary solutions, even when the fundamental remedy is evident.
- Limits to success/growth: Endless growth and unbridled reinforcement inevitably encounter limitations. This archetype emphasises the presence of constraining conditions for reinforcing behaviours, regardless of the effort invested.
- Drifting/eroding goals: When the pressure to meet a goal outweighs the effectiveness of the current actions, lowering the goal becomes a typical response. This gradual lowering of targets results in the system's decline as attention is diverted from addressing the root issue.
- Growth and underinvestment: Neglecting long-term capacity investment while striving for improved performance can limit growth. This archetype highlights the potential to surpass current constraints through timely and sufficient investment.
- Success to the successful: The allocation of shared resources between entities depends on their respective success and performance. However, this leads to an uneven distribution of resources among a shared group, disproportionately favouring the already successful.
- Escalation: Efforts to counteract a threat from another party often intensify the competitive actions, escalating the conflict between the parties involved.
- The tragedy of the commons: When shared resources are overburdened, the entire interconnected system suffers. This archetype illustrates how excessive pressure on common resources can lead to system failure and negative consequences.
- Accidental adversaries: Discrepancies in mental models between two partnering parties can lead to misunderstandings, mistrust, and suspicion. This archetype portrays how shared interests can devolve into accidental opposition due to misinterpreted actions.

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- Attractiveness principle: Evaluating various limiting factors in a system helps determine where initial action is needed. The most critical limitations can be identified and targeted for reduction by comparing influences slowing down system progress.

In summary, these system archetypes serve as invaluable tools to comprehend the complex dynamics of complex systems, offering insights into practical solutions and potential pitfalls within various contexts. System Archetypes can be used as a starting point for SD modelling because they provide an outline framework of a complex system (Oosthuizen, 2021:1-11; Rocha et al., 2020:1-10; Nadiia et al., 2021:123-140; Moallemi et al., 2022:1-21). Archetypes are suitable for complex systems because they support trend and behaviour identification and future consequence recognition in a more holistic approach. For example, if environmental and social factors are not included in the economic system, the global society will experience a collapse with the current unlimited economic system. This unintended consequence of continued economic growth has already been investigated and identified with archetypes in the previous century by, for example, Meadows et al. (1972:2-122). Generic System Archetypes can be identified through problem descriptions of the system.

Some generic archetypes for sustainability include 1) Fixes that Fail, 2) Growth and Underinvestment and 3) Escalation. The Fixes that Fail archetype describes systems where the solution works in the short term, but long-term unintended consequences can require even more effort. The second one mentioned is the Growth and Underinvestment archetype, where a growing action increases, and demand for additional capacity grows. This necessitates an investment; if not actioned, the underinvestment can cause underperformance in the ever-increasing system (Bano et al., 2022:4995-5010). The final archetype discussed is the Escalation archetype; the system involves two connected loops influencing each other directly (Hallett and Hobbs, 2020:1017-1025; Mandl, 2023:135-141).

The activities and results are seen as inputs to each other's efforts. These and more have been described by Senge (2006:389-400). One archetype that combines the three mentioned previously is the Limits to Growth archetype, a present-day archetype developed across several industries, especially the sustainability arena (Qiong et al., 2016:481-489).

The study by Meadows et al. (1972:2-122) has continued to a study called "Beyond the Limits", also by Meadows et al. (1992:3-85) and has been revised with a 30-year update by (Meadows et al., 2006:397-399). The Limits to Growth (LtG) concept spawned by these authors describes how unsustainable, continuous growth is in an interconnected globalised society. The LtG archetype will be used in this study to show how unsustainable decisions prevent or limit the CE, as shown in Figure 18. It shows

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the interaction between a reinforcing loop (R1) and a balancing loop (B2) constrained by external factors. The reinforcing loop (R1) demonstrates that as efforts increase, performance improves, which further encourages more efforts, creating a self-reinforcing cycle. However, as performance grows, it eventually triggers limiting actions due to constraints, forming the balancing loop (B2). These limiting actions work against further performance gains, leading to diminishing returns. This dynamic highlight how initial progress can be hindered by systemic constraints, requiring strategic interventions to overcome limitations and sustain growth. The Growth and Underinvestment archetype is an elaborated LtG representation (Awah et al., 2024:1-17; Mutingi et al., 2017:199-205). The economic influences of the CE are studied in several research areas and fit with the elaborated archetype (OECD, 2017).

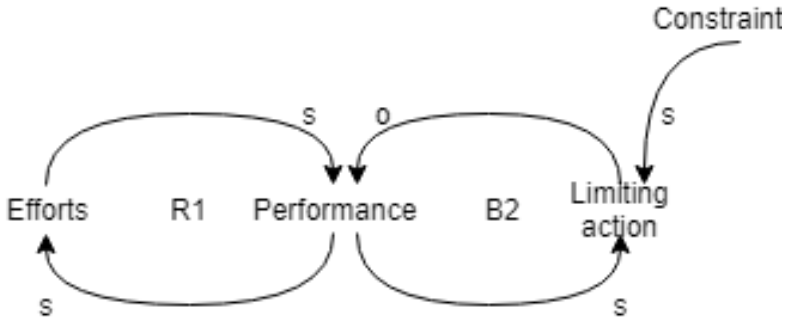

Figure 18. Limits to Growth archetype template - Adapted from (Kim, 1992:2-30)

Some examples of the LtG archetype included market saturation despite increased marketing efforts, metabolic rate decreasing despite increased, prolonged dieting, and service capacity limits on the physical capacity of businesses. Instead of focusing on a single bias and its influence on sustainable decision-making, this study assessed several biased influences on certain phases of the CE (van der Linde et al., 2022:2-11). See Section 3.3.2 for the full model development explanation.

The study further explained in Section 3.3.2 emphasises that the economic disruptions caused by the COVID-19 pandemic have highlighted the need for a new approach, referred to as the "new normal," which requires a deeper understanding of how stakeholders' mental models influence decisions that impact the biosphere and technosphere. A research gap is identified in how cognitive influences on decision-making are integrated into CE models, which currently lack thorough consideration of the social and cognitive dimensions that affect sustainability. Through SD modelling, this research aims to explore and analyse these complex interactions, ultimately proposing a framework that bridges this gap and supports more sustainable decision-making within the CE.

The conclusion asserts that applying a systems approach to the CE is essential for fostering better decision-making processes that support sustainability. The research demonstrates how cognitive biases can significantly influence stakeholder decisions,

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often limiting the effectiveness of sustainability initiatives within the CE. By integrating cognitive biases into SD models, stakeholders can achieve more accurate and sustainable outcomes. Ultimately, the research advocates for continued exploration of decision-making frameworks that incorporate cognitive and behavioural insights, ensuring that CE practices are resilient and adaptive to the complexities of human behaviour.

In Figure 19, cognitive biases that limited sustainable decisions were presented, which restricted the accomplishment of a CE. The limiting factor was the pre-existing biases within consumer behaviour patterns. The leverage point lies in decreasing the biases as much as possible with correct system interventions. The first reinforcing loop showed how the adoption rate of CE models increased a sustainable society, and the increased sustainability-focused society led to an increased adoption rate.

Figure 19 illustrates cognitive biases that impede sustainable decision-making, consequently hindering the advancement of CE initiatives. The root of this limitation stems from entrenched biases within consumer behaviour patterns. The pivotal intervention point lies in minimising these biases through targeted systemic interventions. The initial reinforcing loop delineates how adopting CE models fosters a more sustainable society, leading to increased adoption rates. As societies progress toward sustainability, the balancing loop indicates a diminishing need for sustainable decisions akin to a new business-as-usual paradigm.

Moreover, the balancing loop underscores that heightened consumer awareness of sustainability needs reinforces the societal shift towards sustainability. Within this system, cognitive biases act as a limiting factor, exerting pressure on consumers to embrace or reject sustainable choices. Figure 19 also elucidates external influences on cognitive biases, such as System 1 and 2 thinking and decision-making behaviours, discussed in earlier sections. This Causal Loop Diagram is novel in its application of the 'Limits to Growth' archetype, specifically to sustainable decision-making within the CE, showcasing how cognitive biases can influence the tipping points of sustainability efforts. The model development of this figure is explained in Section 3.3.2. As depicted in Figure 19, these external factors encompass situational and social awareness, both deemed critical components.

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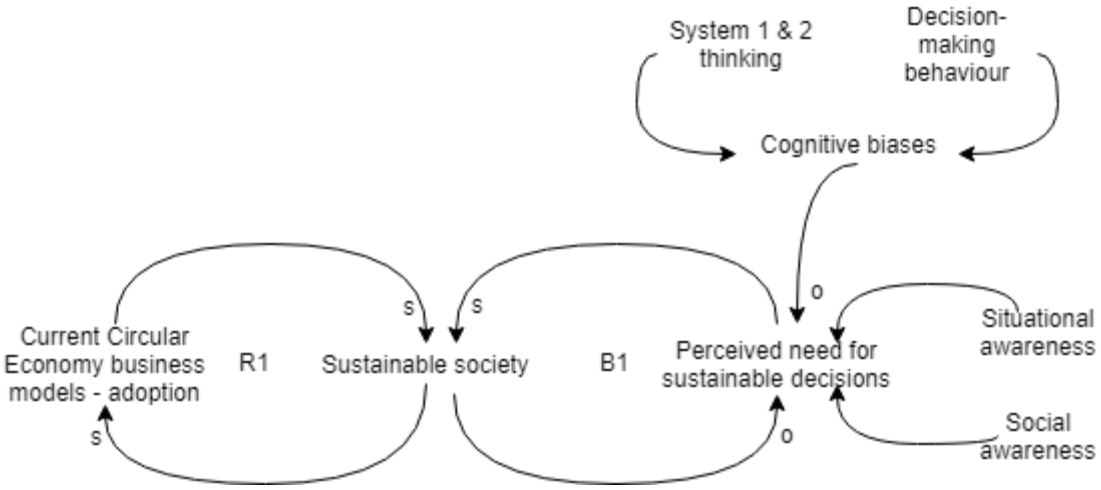

Figure 19. Limits to Growth archetype applied to sustainable decision-making. (van der Linde et al., 2022:2-11)

The first research question explained in Section 1.6, exploring the extent to which biases are prominent in sustainable decision-making, is comprehensively addressed in the paper "A systems approach to understanding cognitive bias influences on stakeholders in the Circular Economy." This study by the current researcher employs the Limits to Growth archetype to illuminate how cognitive biases impact the decisions of various stakeholders engaged in sustainability efforts. Through a detailed conceptual model discussed in Section 3.3.2, the model demonstrates that negative biases such as overconfidence, confirmation bias, and status quo bias significantly hinder the effectiveness of sustainable decision-making. These biases create feedback loops that reinforce unsustainable practices despite stakeholders' intentions to promote sustainability. The Limits to Growth archetype reveals how initial successes in sustainability can lead to complacency, causing long-term growth limitations and systemic challenges that impede further progress.

The model highlights the complex dynamics between cognitive biases and sustainable decision-making by applying system archetypes and constructing a conceptual model. The model illustrates that while stakeholders may initially achieve some sustainability goals, their cognitive biases can lead to actions that eventually constrain further advancements. For instance, overconfidence in early achievements can result in reduced vigilance and adaptive capacity, making the system vulnerable to unforeseen challenges. Confirmation bias may cause stakeholders to selectively interpret information in ways that validate their preconceptions, ignoring critical data that could inform better decisions. The study underscores the necessity of recognising and mitigating these biases to foster more resilient and effective sustainable practices within the CE. By bringing these cognitive influences to light, this thesis provides valuable insights for policymakers, businesses, and researchers aiming to enhance the sustainability of their decisions and actions.

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As societies became more sustainable, the balancing loop indicated the need for sustainable decisions decreased. This resembles a new business-as-usual approach (Meadows and Rome, 1974:205). The balancing loop also illustrated that consumers' importance lay heavily enough to ensure a more sustainable society when the perceived need for sustainable choices increased. The limiting factor in this system was the cognitive biases that created or removed pressure on consumers to make sustainable decisions. An expansive number of biases could influence consumer behaviour. What was also presented in Figure 19 were the external influences on cognitive biases such as System 1 and 2 thinking and decision-making behaviours. The two thinking systems, termed System 1 and System 2, are based on research done by psychologists Daniel Kahneman and Amos Tversky (Kannengiesser and Gero, 2019:2-10).

System 1 is intuitive and automatic, involving quick, effortless judgments based on prior experiences and emotions. System 2 is analytical and deliberate, requiring conscious effort and logical reasoning to solve complex problems or make decisions. These two systems work together; System 1 provides initial responses, while System 2 steps in for more critical thinking tasks. See Section 9.5 for future recommendations with AI as a digital System 2 thinking.

The archetype serves the purpose of depicting the fundamental framework of a system. This instance demonstrates that embracing and advancing diverse CE business models and effectively managing constraints to attain desired outcomes can contribute to establishing a sustainable society. The development should be balanced between social, economic, and environmental.

The journey toward a smooth transitioning system is often complex and multifaceted, requiring a strategic approach considering present needs and future aspirations. The concept of The Three Horizons provides a valuable framework for navigating this transformation, as shown in Figure 20. Initially introduced by Bill Sharpe, this model suggests that effective transitions involve three distinct phases or "horizons," each with unique characteristics and challenges (Sharpe, 2020:9-24). These horizons offer a strategic perspective that aligns well with the insights from the "Limits to Growth" archetype, which underscores the necessity of balancing growth with sustainable limitations.

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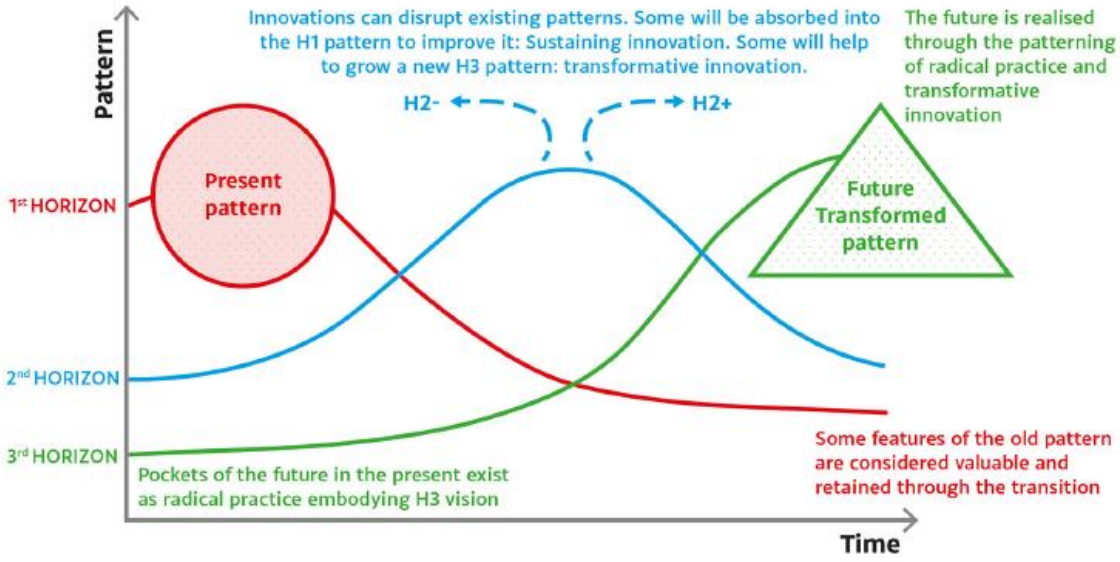

Figure 20. The Three Horizons representation of smooth system transition (Fazey and Leicester, 2022:5-11)

Another example where archetypes have been used in the sustainability field is where Kueppers et al. (2021:2-16) analysed different countries' energy systems. The authors modelled different decarbonisation strategies and found that an adequate system approach makes the global transition possible.
The archetype is further developed as input to a CLD and an SFD to evaluate the system's dynamic properties of gamma changes. The archetype is also used to create a decision framework tailored for the CE, as seen in 3.3.2. The model development sections in Chapter 3 discuss the model phases.

In conclusion, exploring the current archetypes available for sustainability provides a rich and insightful framework for understanding the intricate dynamics of complex systems. These archetypes are valuable tools for illuminating recurring patterns and behaviours within various contexts. From the "Fixes that Fail" archetype, cautioning against superficial solutions, to the "Limits to Success/Growth" archetype, highlighting the need for balance and constraints, each archetype offers a distinct lens through which we can analyse the challenges and opportunities of achieving sustainability.

As people navigate the complexities of a rapidly changing world, these archetypes empower us to approach sustainability holistically. They remind us of the interconnectedness of actions and consequences, urging us to consider the long-term implications of our decisions. Moreover, they emphasise the significance of adaptability, stakeholder engagement, and continuous learning in pursuing sustainable practices.

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The versatility of these archetypes extends beyond theoretical understanding; they provide practical insights for devising effective strategies, guiding decision-making, and mitigating unintended consequences. By integrating these archetypes into the sustainability efforts, modellers equip themselves with a more comprehensive toolkit for addressing the multifaceted challenges of our time.

In the ongoing journey towards a more sustainable future, the archetypes the research has explored offer enduring wisdom. They encourage people to navigate complexity with clarity, to view challenges as opportunities for growth, and to ensure that the pursuit of sustainability is not only visionary but also grounded in the principles of ST.

2.4.4. Causal Maps and System Dynamic Modelling

CLDs are graphical representations that model and visualise system feedback structures. By illustrating the cause-and-effect relationships and feedback loops, these diagrams enable researchers to analyse how changes in one part of the system can propagate and influence other elements. CLDs aid in identifying unintended consequences and understanding the dynamic behaviour of systems, helping inform decision-making for sustainability interventions (Richardson, 2011:219-243).

ST and SD are vital in generating sustainable value through modelling. Hjorth and Bagheri (2006:74-92) emphasise another significant aspect, suggesting that SD can pinpoint leverage points within systems where even minor adjustments can yield substantial impacts. Practitioners utilise ST concepts within SD to enhance decision-making in complex, dynamic systems, focusing on interconnectedness, resilience, and emergence properties (Williams et al., 2017:866-881). ST facilitates a comprehensive understanding of real-world systems, emphasising the interrelationships among variables. Central to ST are mental models, capturing system interpretations through archetypes, non-linear behaviour, and feedback loops (Jackson, 1994:213-229). SD complements ST by quantifying these connections, offering a time-dependent depiction of system behaviour. This approach utilises models to simulate behavioural changes, unveiling subtle connections, dynamic properties, delays, and unintended consequences.

SD is crucial in interdisciplinary systems and is prevalent in nearly all domains (Bureš, 2019). Two distinctive diagrams, CLDs and Stock and Flow Diagrams (SFDs), are employed within SD. The extensive literature on these diagrams details their logic, applications, and advantages (Fenton and Neil, 2011:10-21; Baghaei Lakeh and Ghaffarzadegan, 2016:309-331; Sterman, 2002). SFDs facilitate quantitative modelling, allowing for simulation and analysis, while CLDs serve qualitative modelling purposes. Geels et al. (2017:1242-1244) caution that ambitious strategies for sustainable decision-making may face systemic challenges due to stakeholder reactions. SD offers a systemic approach to address the complexity and dynamics of

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the CE. This thesis closes this gap by modelling the CE as an STS using SD, aiming to enhance systemic understanding and inform sustainable decision-making methodologies.

Behavioural operational research (BOR) focuses on the interactions between humans and systems, exploring how cognitive processes impact systems (Lane and Rouwette, 2022). This emerging field finds application within supply chain research, addressing decision-making problems by integrating behavioural dimensions (Brocklesby, 2016:796-805). Such challenges involve complex interactions among systems, individuals, and real-world contexts, creating complex and dynamic scenarios. In cases marked by ambiguity, lacking immediate solutions and dynamic shifts, a practical approach often involves a systems methodology that accommodates human cognitive processes (Forrester et al., 2018:61-75; Oosthuizen, 2014).

SD research has traditionally been dedicated to assessing policies and strategies, employing modelling techniques to analyse systems comprehensively. Notably, SD is an approach for evaluating complex dynamic issues, concurrently delving deeper into exploring behavioural considerations that impact decision-making, actions, and repercussions (Alessi and Kopainsky, 2015:223-229). This trend has catalysed the emergence of Behavioural System Dynamics (BSD), a distinct research stream focusing on the interplay of behavioural aspects within the SD framework (Barnabè and Davidsen, 2019:339-364). Scholarly discourse underscores that SD offers an indispensable tool for simulating complex scenarios, particularly those featuring variables, structural complexities, and environmental influences. Indeed, the complexity of such systems often stems from their social components, as highlighted by Forrester et al. (2018:61-75).

Against this backdrop, the imperative arises to construct representative models of systems as accurately as possible, aiming to enhance decision-making and overall system (Gary and Wood, 2011:569-594). Employing models is a sophisticated and holistic approach, persuading decision-makers to opt for sustainable choices. As the research landscape evolves, integrating BOR, SD, and behavioural insights is essential for achieving a comprehensive understanding of complex systems and fostering improved decision-making for sustainability.

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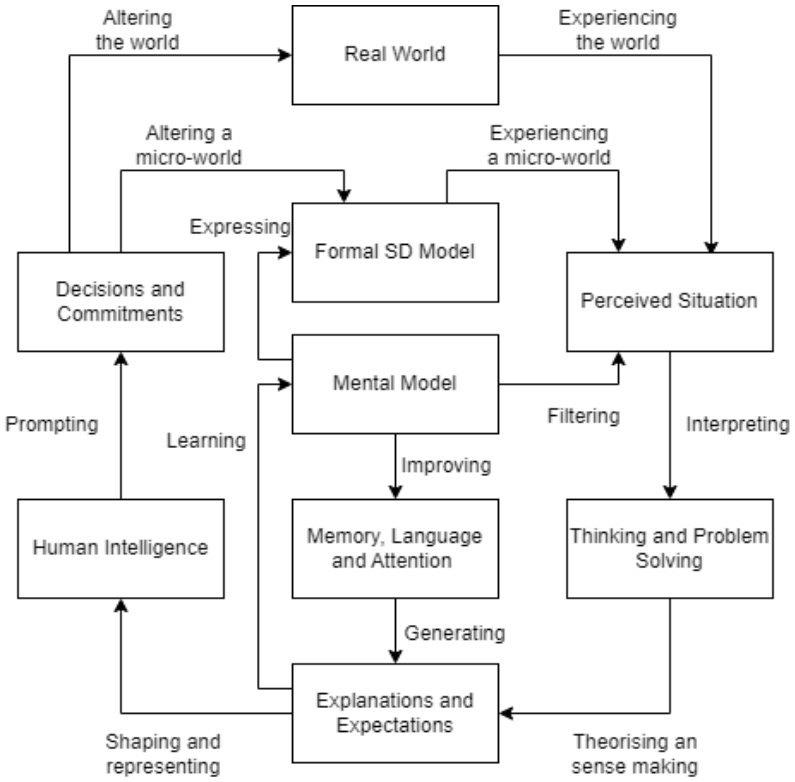

Figure 21. Cognitive effects of humans in systems and behavioural influences on decision-making (Lane and Rouwette, 2022; Solso et al., 2005; Sterman, 2002)

The links between the real world and perceived situations become evident in Figure 21. The diagram illustrates that essential decisions and practical problem-solving skills are central in reshaping the perceived situations and the actual world. In the subsequent subsection, another vital theoretical element is introduced, focusing on the ongoing discourse regarding decision-making models for sustainable systems and the trajectory towards achieving sustainability.

2.4.5. Decision-making Models

Analytics and decision support tools, such as decision support systems (DSS), aim to enhance decision quality through various means. This includes leveraging communication technologies, collecting and processing data, aiding in data and document analysis, utilising quantitative models to detect and address issues, accomplishing tasks within decision processes, and providing guidance throughout the decision-making journey (Phillips-Wren et al., 2019:63-66).

Various decision-making models, such as Multi-Criteria Decision Analysis (MCDA), Analytic Hierarchy Process (AHP), and decision trees, provide structured frameworks for evaluating alternative courses of action in sustainability contexts (Kasin et al., 2023:48). These models consider multiple criteria, preferences, and uncertainties to facilitate transparent and informed decision-making, enabling stakeholders to weigh environmental, social, and economic factors when choosing sustainable solutions (Kwakkel et al., 2016:168-183).

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In DSR, these decision support tools can be utilised during the design and evaluation phases to assess alternative solutions and select the most effective design artefacts. MCDA enables stakeholders to consider multiple criteria simultaneously when evaluating different design options, allowing for a comprehensive assessment of trade-offs and preferences. AHP, on the other hand, structures complex decision problems hierarchically, facilitating the decomposition of decision criteria into manageable components and enabling stakeholders to compare alternatives systematically based on their relative importance. Decision trees visually represent decision-making processes, mapping out possible outcomes and their associated probabilities, helping stakeholders identify optimal courses of action.

Similarly, these decision support tools can be employed in SD to model decision-making processes within dynamic systems and simulate the impacts of different decisions over time. MCDA can be integrated into SD models to capture the preferences of various stakeholders and incorporate their priorities into decision-making processes. AHP can aid in structuring the decision-making hierarchy within SD models, ensuring that decision criteria are appropriately prioritised and weighted. Decision trees can represent decision pathways within SD models, facilitating the exploration of different decision scenarios and their consequences on system behaviour.

In the following section, decision-making models are explored further. By examining and integrating these diverse models into sustainability research, scholars and practitioners can comprehensively understand the complex interplay between ecological, social, and economic dimensions, fostering a more holistic and resilient approach to decision-making for a sustainable future.

2.5. Current Decision-Making Methods

Decision-making is integral to human life and organisational processes, shaping the trajectory of actions and outcomes in various domains. To navigate the complexities of decision-making, researchers and practitioners have developed many decision-making models that provide structured frameworks to analyse options, assess risks, and make informed choices (Milkman et al., 2009:379-383).

2.5.1. Internal and External Stakeholders

In decision-making models, stakeholders can be categorised into two main groups: internal and external. Internal stakeholders are individuals or groups within an organisation directly involved in the decision-making process or are affected by the decisions made. External stakeholders, on the other hand, are individuals or groups outside the organisation but are impacted by the decisions made by the organisation (Greer et al., 2023:693-718; Velter et al., 2020:2-7). The visual representation of this can be seen in Figure 1 at the beginning of this thesis. Understanding the perspectives

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and needs of both internal and external stakeholders is crucial for effective decision-making, particularly in sustainability, where decisions can have far-reaching consequences on the environment, society, and the economy.

Internal stakeholders typically include employees, managers, executives, and board members. They are directly involved in decision-making and may have different roles and responsibilities in contributing to the final decision. The engagement and buy-in of internal stakeholders are critical for successfully implementing decisions. For instance, decision-making models like the AHP encourage involving internal stakeholders to provide their inputs and preferences during decision-making (Wind and Saaty, 1980:641-658; Canco et al., 2021:1-15; Sharma et al., 2020:203). This collaborative approach can help identify the most suitable and sustainable options that align with the organisation's goals and values.

External stakeholders encompass a broader range of individuals or groups beyond the organisation. They can include customers, suppliers, investors, government agencies, local communities, and non-governmental organisations. Organisations' decisions can significantly impact these external stakeholders, especially in the context of sustainability. Models like the Stakeholder Analysis from Freeman (2020:657-671) help identify and assess various external stakeholders' interests, concerns, and influence. Organisations can foster greater transparency, accountability, and sustainability in their actions by involving external stakeholders in decision-making and considering their perspectives.

Incorporating the perspectives of both internal and external stakeholders is crucial for sustainable decision-making, as previously shown in Figure 1. In sustainability initiatives, decisions must balance environmental, social, and economic considerations to achieve long-term success and resilience. Engaging internal stakeholders ensures that sustainability values are embedded within the organisation's culture and operations, leading to more cohesive and aligned decision-making. On the other hand, involving external stakeholders allows organisations to consider broader impacts, anticipate potential risks, and identify opportunities for collaboration and shared value creation. By embracing a stakeholder-centric approach and utilising decision-making models incorporating stakeholder inputs, organisations can foster sustainable practices, contribute positively to society and the environment, and achieve lasting success in pursuing a sustainable future.

These models offer valuable insights into the decision-making process, considering uncertainty, preferences, and trade-offs. In this thesis, the research delves into the world of decision-making models, exploring their diverse methodologies and applications across different contexts. From the classic normative models like Rational Choice Theory to the multi-criteria approaches of the AHP and the dynamic

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perspectives of decision trees, these models empower individuals and organisations with the tools to optimise their decision-making processes and navigate complex challenges (Saaty, 1990:9-26; Pasman et al., 2022:2-6; Štofková et al., 2022:1-6; Tavana et al., 2023:879-907). Understanding the strengths and limitations of these models is essential for researchers and decision-makers alike as they strive to make impactful and well-informed choices in the face of ambiguity and uncertainty. Through this exploration, the research uncovers the art and science of decision-making models and their role in shaping a sustainable and resilient future.

MCDA is a systematic decision-making approach to evaluate and compare multiple options or alternatives across several criteria or attributes (Zlaugotne et al., 2020:454-471). When decisions involve complex and conflicting factors, MCDA provides a structured framework to facilitate informed choices. It allows decision-makers to quantitatively and qualitatively assess options by assigning weights to different criteria, considering their relative importance, and scoring alternatives accordingly. MCDA aims to bring transparency, objectivity, and a comprehensive perspective to decision-making processes, mainly when dealing with multidimensional and interrelated considerations, as seen in Figure 22. It is commonly employed in various fields, including business, engineering, environmental management, healthcare, and public policy, to guide choices that align with specific goals and preferences (Zanghelini et al., 2018:609-622).

The AHP is a structured decision-making methodology developed by Saaty (2005:1-36). It is designed to help individuals or groups systematically evaluate and prioritise multiple criteria and alternatives when faced with complex decisions. AHP involves breaking down a decision problem into a hierarchical structure, where the top level represents the main objective or goal, and the subsequent levels consist of criteria, sub-criteria, and alternatives (Kalutara et al., 2018:37-50). AHP enables decision-makers to make pairwise comparisons between criteria and alternatives using a scale of relative importance, as seen in Figure 23. These comparisons are converted into numerical values that reflect the preferences and priorities of the decision-maker. A mathematical process is then applied to compute the overall scores of each alternative based on the hierarchical structure and the relative weights assigned to the criteria. The key benefits of AHP include its ability to handle both quantitative and qualitative data, its transparency in decision-making, and its capacity to accommodate subjective preferences while maintaining a structured framework. AHP finds applications in various domains, such as project selection, resource allocation, strategic planning, and supplier evaluation, helping to make more informed and consistent decisions in complex scenarios (Erdinç et al., 2024:688-703; Timóteo et al., 2024:69-90; Maceika et al., 2021:1-32).

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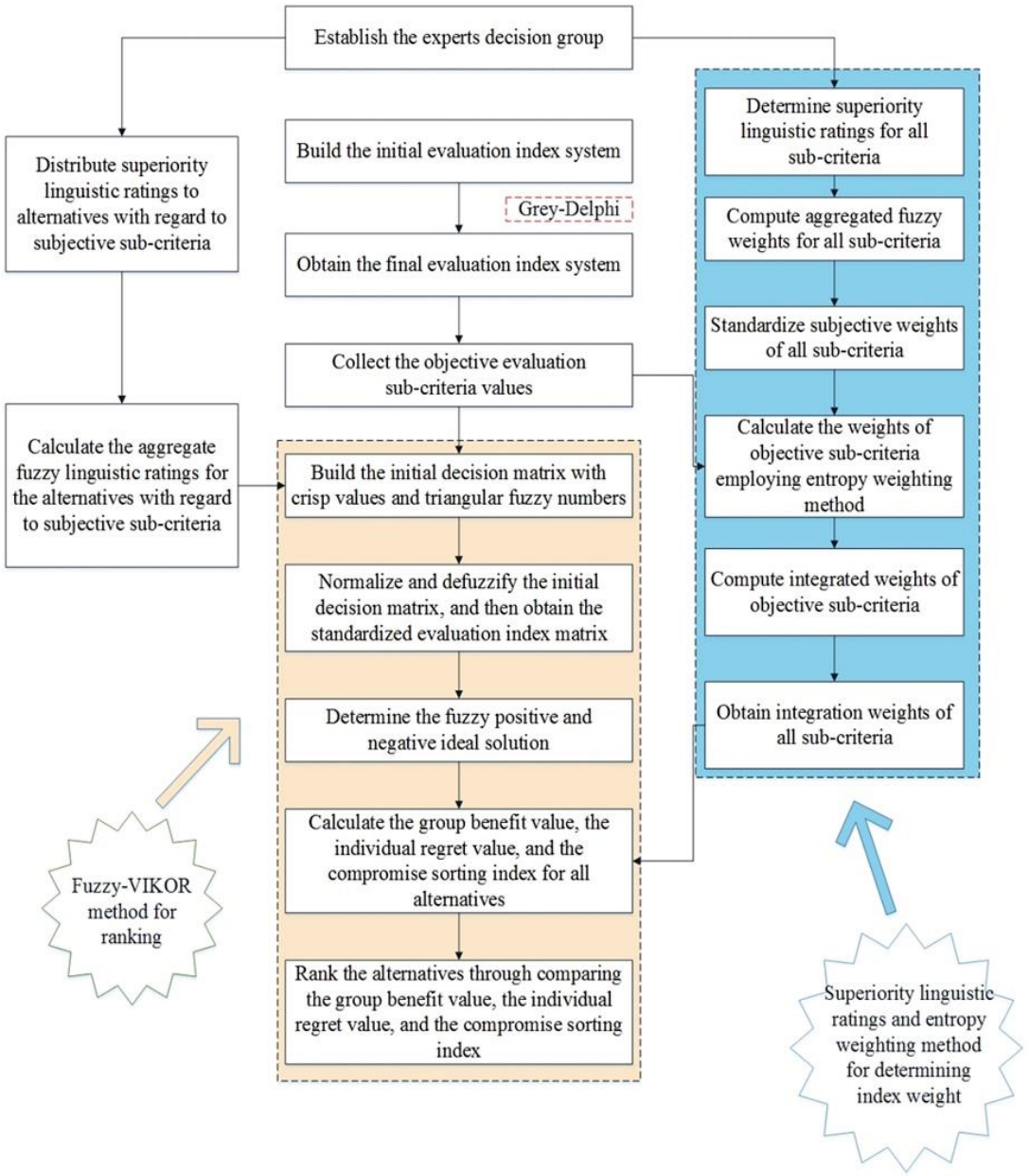

Figure 22. Multi-criteria decision-making approach for CE example. (Zhao et al., 2017:2262-2276)

Decision trees are a graphical representation and modelling technique used in decision analysis and machine learning. They visually depict a decision-making process as a tree-like structure, where each node represents a decision or an event, and branches represent possible outcomes or choices. Decision trees are beneficial for making decisions based on multiple criteria, uncertainties, and potential consequences.

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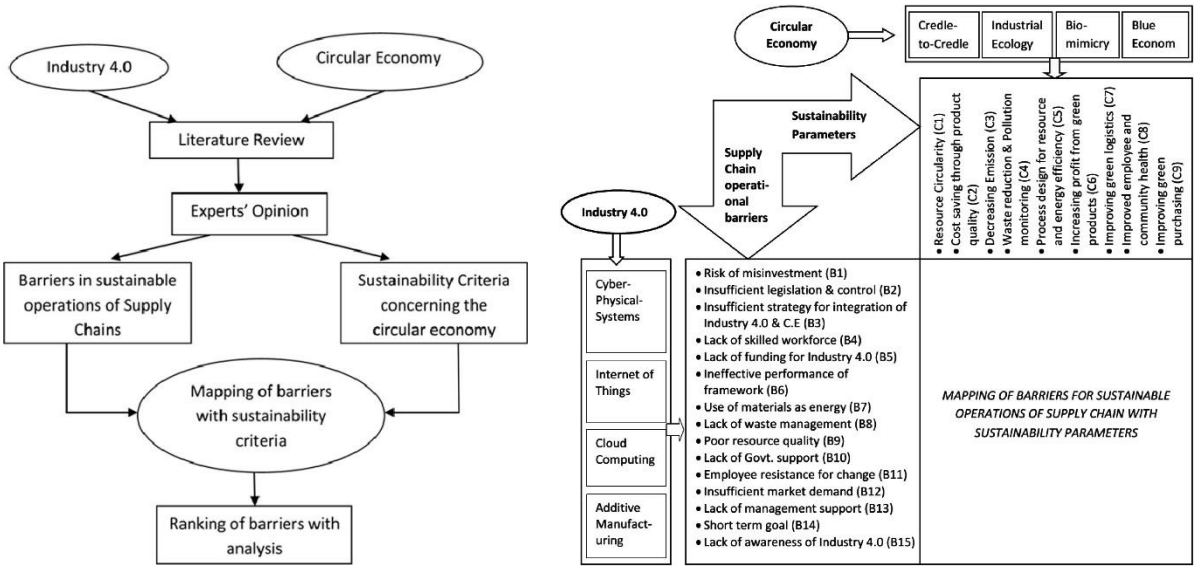

Figure 23. AHP was applied to CE to analyse barriers. (Kumar et al., 2021:105215)

Decision trees help analyse complex scenarios by breaking them into more straightforward, sequential choices. They incorporate quantitative factors, probabilities, and uncertainties at each decision point to guide optimal decision-making. Decision trees are also widely used in machine learning for classification and regression tasks, where they learn patterns and relationships in data to make predictions (Bockstaller et al., 2017:130-144). By visually mapping out decisions and their potential consequences, decision trees offer a structured approach to complex decision-making, aiding in understanding trade-offs, risks, and outcomes associated with different choices.

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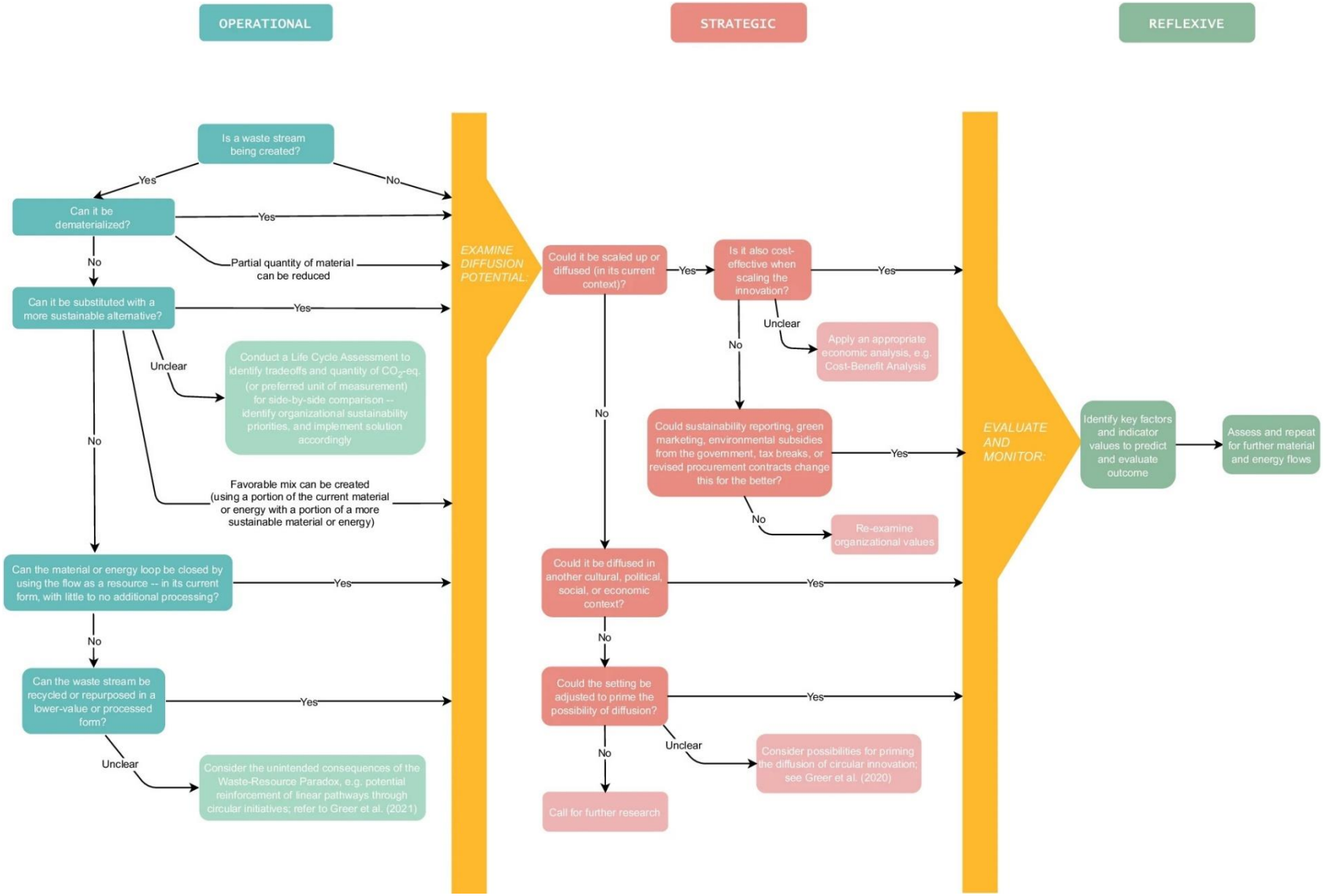

Figure 24. The Circular Decision-Making Tree from (Greer et al., 2023:693-718)

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In their research, Greer et al. (2023:693-718) combined theories from CE, transition management, industrial ecology, and decision-making to construct a framework for decision-making aimed at advancing a CE. By advocating for a fresh decision-making paradigm and providing a practical tool for navigating this approach across policy, practice, and society, the study sought to close the divide between scientific literature and real-world implementation. The outcome was the development and design of the CDMT framework shown in Figure 24.

One thing to note throughout this study is that regulating the decisions of these stakeholders is not the only solution. In their book ‘Cradle to Cradle: Remaking the Way We Make Things’, McDonough and Braungart (2002:202) state that a regulation signals design failure. It is what we call a license to harm: a permit issued by a government to an industry so that it may dispense sickness, destruction, and death at an "acceptable" rate.

Having explored the pivotal roles of internal and external stakeholders in decision-making processes, the research now focuses on establishing system requirements and reference models. While stakeholders provide essential perspectives and inputs, translating these insights into actionable system requirements and reference models is critical for designing effective solutions. In this next section, the research delves into the methodologies and considerations involved in defining system requirements and developing reference models, elucidating how these processes contribute to aligning organisational objectives with stakeholder needs and realising sustainable outcomes (Velter et al., 2020:2-7; Attanasio et al., 2022:860-874).

The link between the CE and decision-making methods is fundamental to ensuring sustainable practices within industries. In transitioning from a linear to a circular model, decision-making requires tools and frameworks incorporating stakeholder engagement, resource management, and long-term sustainability goals. According to Salvioni and Almici (2020:1-29), CE involves the physical reorganisation of material flows and the strategic rethinking of how decisions are made to integrate social, environmental, and economic dimensions. This strategic rethinking often involves participatory decision-making processes that emphasise collaboration among stakeholders to foster transparency and mutual accountability, essential for the successful implementation of circular models.

Moreover, decision-making in CE must account for the complex interrelations between stakeholders, such as businesses, governments, and consumers, as highlighted by Salvioni and Almici (2020:1-29). This requires adopting decision-making frameworks that facilitate dialogue and collaboration, as these interactions are crucial for addressing the multifaceted challenges of sustainability. For instance, decision-support tools that integrate sustainability metrics can help managers and policymakers

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evaluate the long-term impacts of their choices, thus aligning short-term actions with broader sustainability objectives. By incorporating these methods, decision-making in the CE can be more inclusive and better equipped to handle the uncertainties and complexities inherent in managing finite resources.

2.5.2. System Requirements and Reference Models

Establishing system requirements and reference models is essential to ensure that these models effectively address the complexities of decision-making processes. System requirements define the vital characteristics and capabilities that a decision-making model must possess to meet its intended objectives. Reference models serve as structured frameworks or templates that guide the development and implementation of decision-making models, providing a standardised approach for various applications.

System requirements for decision-making models include accuracy, transparency, adaptability, scalability, and inclusivity. Decision-making models must accurately represent the problem, incorporate relevant data, and provide valid and reliable outputs. Transparency ensures that the decision-making process is straightforward and understandable to stakeholders, promoting trust and acceptance of the decisions made. Adaptability allows decision-making models to accommodate changes in the decision context or input data, ensuring their relevance over time. Scalability ensures that the model can handle varying levels of complexity and data volumes. Inclusivity involves considering diverse perspectives and stakeholders to ensure that decisions reflect a broad range of interests and values (Karschin and Geldermann, 2015:305-314).

Reference models in decision-making provide standardised structures or methodologies that guide the development and implementation of decision-making models. The AHP is a widely used reference model, described in 2.5.1 and Figure 23. This reference model has applications in various fields, including sustainability assessment (Lee, 2016:13-16).

Another prominent reference model mentioned in 2.5.1 and Figure 22 is the MCDA, which encompasses various decision-making methods like the Weighted Sum Model and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). MCDA allows decision-makers to consider multiple criteria and their relative importance when evaluating options, making it valuable for sustainability decision-making, where environmental, social, and economic factors must be weighed, as seen in another MCDA process illustrated in Figure 25 (Belton et al., 2002:331-343).

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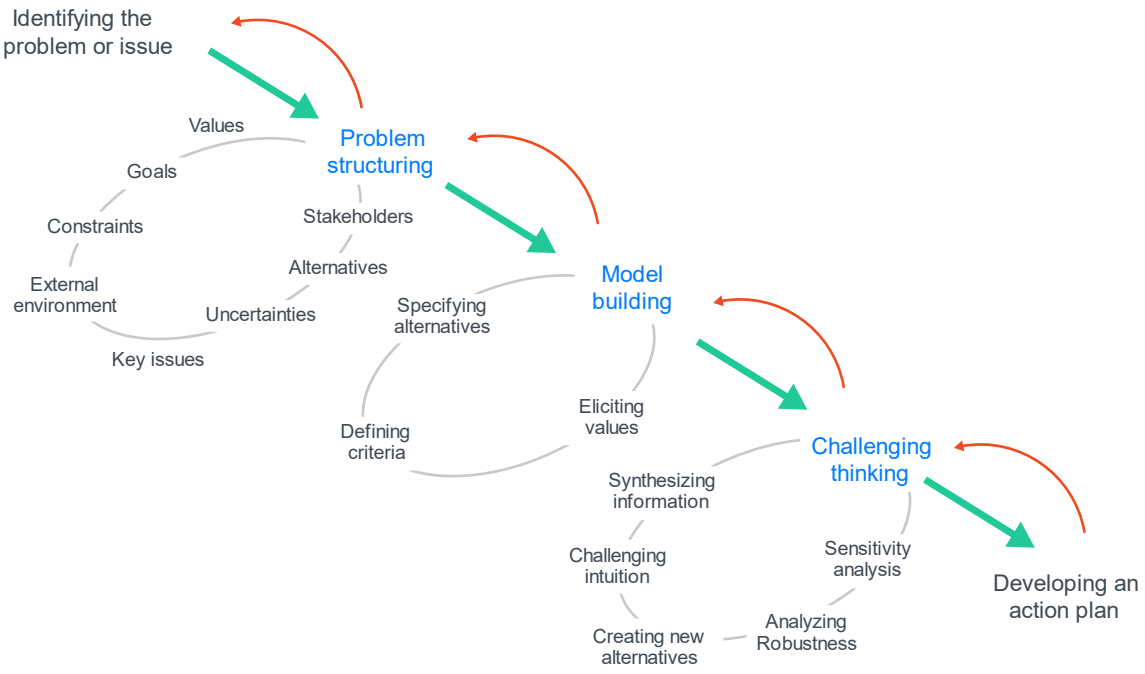

Figure 25. The Process of MCDA from (Belton and Stewart, 2010:209-239)

In the context of DSR, MCDA is crucial in the design and evaluation phases. MCDA allows researchers to systematically evaluate alternative design options based on multiple criteria or objectives, facilitating the selection of the most suitable solution. This link between MCDA and DSR can be described as an iterative design process within DSR and the integration of MCDA at crucial decision points.

The DSR process is a cyclical loop, starting with problem identification and followed by design, implementation, and evaluation phases. At each decision point within this loop, MCDA is integrated to assess alternative design options based on predefined criteria and stakeholder preferences. MCDA helps researchers prioritise design alternatives, identify trade-offs, and ultimately select the most optimal solution. Additionally, feedback loops between the evaluation phase and earlier stages of the DSR process explain how insights gained from MCDA-informed evaluations inform subsequent iterations of the design process. This integrated approach ensures that the final design artefacts produced through DSR are innovative and aligned with stakeholder needs and preferences.

Developing decision-making models with sound system requirements based on robust reference models is crucial for sustainable decision-making. Accurate and transparent models can help identify sustainable solutions that holistically address environmental, social, and economic aspects. Adaptive and scalable models ensure that decisions

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remain relevant and practical despite evolving sustainability challenges. Inclusive models considering diverse stakeholder perspectives promote the acceptance and implementation of sustainability initiatives. By adhering to system requirements and leveraging appropriate reference models, decision-making models can foster sustainable practices, support achieving environmental and social goals, and create a more sustainable and resilient future.

2.5.3. Barriers and Success Factors of Sustainable Decision-making

Sustainable decision-making models are crucial in addressing complex environmental, social, and economic challenges. However, their effectiveness can be influenced by various barriers and success factors. One significant barrier is the availability and quality of data required for sustainable decision-making. A lack of reliable and comprehensive data can hinder the accuracy and reliability of models, leading to suboptimal decisions (Olabode and Bakare, 2020; Morse et al., 2002:13-22).

Additionally, some sustainable decision-making models can be complex and challenging to interpret, making it difficult for stakeholders to understand and trust the model's outputs (Dewulf and Van Langenhove, 2006:339). Resistance to change within organisations or among stakeholders can also impede the adoption of sustainable decision-making models, particularly if they challenge established practices or interests (Bansal, 2005:197-218). Moreover, inadequate involvement of diverse stakeholders can lead to decisions that do not adequately consider the broader social and environmental implications (Ison et al., 2013:34-42). Furthermore, decision-making models prioritising short-term gains over long-term sustainability can result in decisions that are detrimental to the environment and society in the long run (Boyle et al., 2013:166-189).

On the other hand, critical success factors can enhance the impact of sustainable decision-making models. Transparent and well-documented decision-making models build trust among stakeholders, strengthening the acceptance and credibility of the model's outputs (Mendoza and Martins, 2006:1-22). Flexibility and adaptability are also essential traits of successful models, as they allow for incorporating new data or emerging issues, ensuring that the models remain relevant over time (Hämäläinen, 2015:244-253). Involving diverse stakeholders and fostering collaboration can ensure that decision-making models consider various perspectives and interests, leading to more sustainable outcomes (Stirling, 2008:262-294).

Moreover, decision-making models integrating environmental, social, and economic criteria enable a comprehensive evaluation of sustainability impacts and support more balanced and informed decisions (Singh et al., 2022:2-13). Aligning sustainable decision-making models with existing policies and regulations enhances the likelihood of their implementation and impact on sustainability goals (Cordella et al., 2023:3-8).

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Identifying and overcoming barriers while leveraging success factors in sustainable decision-making models is crucial for promoting sustainability. By addressing data limitations and improving data quality, decision-makers can make more informed choices that support sustainable practices. Simpler and more interpretable models enhance stakeholders' understanding and confidence, encouraging adoption. Engaging diverse stakeholders fosters greater acceptance of decisions and aligns them with broader social and environmental interests. Incorporating long-term considerations and multiple criteria supports sustainable outcomes, ensuring that decisions do not compromise future generations' well-being. Recognising these barriers and success factors empowers decision-makers to leverage sustainable decision-making models as powerful tools for achieving a more sustainable and resilient future.

Linking decision-making to cognitive biases is crucial in understanding the limitations and challenges of implementing CE strategies. As discussed in previous sections, cognitive biases can significantly affect decision-making processes by influencing how stakeholders perceive and act upon information. For instance, biases such as confirmation bias and status quo bias can lead decision-makers to favour familiar or traditional linear economy practices, even when evidence supports the benefits of a circular approach.
Cognitive biases often shape how individuals and organisations evaluate risks and benefits, leading to decisions that might undermine long-term sustainability. For example, anchoring bias can cause decision-makers to rely too heavily on initial information, such as cost estimates for traditional practices, without fully considering the long-term savings and environmental benefits associated with CE models. This links back to the decision-making frameworks highlighted earlier, where methods like descriptive statistics and thematic analysis are employed to discern patterns and insights into how these biases manifest and impact sustainability-related attitudes and behaviours.

By integrating decision-making tools that account for cognitive biases, decision-makers can better navigate these biases and make informed, balanced decisions that align with the objectives of the CE. This approach ensures that the biases identified earlier in the thesis are highlighted and addressed through practical, bias-aware decision-making frameworks.

2.6. Chapter Summary

In conclusion, the literature review highlights the significance of sustainable decision-making models in addressing complex environmental, social, and economic challenges. The research identifies various barriers that can hinder the effectiveness of these models, including data availability and quality, complexity, resistance to

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change, limited stakeholder engagement, and short-term focus. On the other hand, the review identifies critical success factors that enhance the impact of sustainable decision-making models, such as transparency and trust, flexibility and adaptability, inclusivity and collaboration, integration of multiple criteria, and policy alignment.

This literature survey, therefore, not only positions the research within the existing body of knowledge but also ensures that the problem is clearly defined and grounded in relevant research, as seen in Table 4. The insights gained during this stage directly inform the subsequent phases of the DSR cycle, particularly the formulation of the artefact (model development) and evaluation stages. In essence, the awareness generated through the literature survey is pivotal for guiding the entire DSR cycle, ensuring that the research addresses pertinent issues and contributes meaningful solutions to the domain of sustainable decision-making.

The review of relevant literature and current models emphasises overcoming these barriers and leveraging success factors to promote sustainability. Each thematic analysis and literature synthesis within this chapter represents a critical research step, providing the foundational knowledge necessary for the subsequent design and refinement cycles.

Table 4. Literature review summary of themes, gaps and references

Themes identified in the literature review	Gaps identified within the themes	References
Background of sustainability	Limited research addressing the social dimension of sustainability, particularly focusing on cognitive and psychological factors influencing decision-making. Most studies focus on environmental and economic aspects (e.g., resource efficiency and waste management).	(Geissdoerfer et al., 2017:757-768), (Savaget et al., 2019:878-892), (Skene and Murray, 2015:480), (Zavos et al., 2024:11)
Background of systems engineering and systems thinking	Limited integration of SE with cognitive and psychological models. Lack of application of ST to understand human decision-making processes in sustainability contexts.	(Sterman, 2000:982), (Jackson, 1994:213-229), (Bahill and Madni, 2023:195-256)
Background of cognitive biases	Gaps in empirical studies explore how specific cognitive biases impact sustainability-related decision-making, particularly in industries transitioning to a CE.	(Tversky and Kahneman, 1974:1124-1131), (Korteling et al., 2023:1-14), (Gonella et al., 2024:141062), (Oschinsky et al., 2021:101611)

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Themes identified in the literature review	Gaps identified within the themes	References
Background of Design Science Research	While DSR is widely applied in information systems, its application in sustainability contexts, especially regarding sustainability-related cognitive biases, is still underdeveloped.	(Hevner et al., 2024:1-10; Peffers et al., 2006; Hunziker and Blankenagel, 2024:97-116)
Importance of sustainability	Studies often neglect the role of social sustainability in decision-making frameworks. Limited literature also links sustainability directly to cognitive biases affecting individual or organisational behaviour.	(Salvioni and Almici, 2020:1-29; Toșa et al., 2024; Sajjad et al., 2024:2849-2867)
Why systems engineering is useful	Lack of research on integrating behavioural models and SE in sustainability practices. This creates a gap in using SE to address human decision-making processes affected by biases.	(Bahill and Madni, 2023:195-256; Yang and Cormican, 2021:81; Steiber, 2016:190-204)
ST approaches	Few studies apply ST to model cognitive biases within decision-making processes related to sustainability. Most focus on environmental and economic aspects.	(Carey et al., 2015; León, 2008:15-20; Sterman, 2002; Challender, 2000:S78-S80)
SD approaches	Limited focus on BSD that incorporates human cognitive biases in sustainability decision-making models.	(Kunche and Mielczarek, 2021:1464; Guzzo et al., 2019; Mutingi et al., 2017:199-205)
Influences of cognitive biases on decision-making	Gaps in practical applications that address how specific cognitive biases can be mitigated to improve decision-making in CE transitions.	(Phillips-Wren et al., 2019:63-66; Maule and Maule, 2016:1-10; Ehrlinger et al., 2016)
Identification of representative cognitive biases	Limited studies identify context-specific biases that impact sustainability-related decision-making, particularly in different industry sectors.	(Montibeller and Von Winterfeldt, 2015:1230-1251; Eberhardt-Toth and Wasieleski, 2013:735-751; Kim and Byung-Kwan, 2004:2-7)
Background of systems engineering and systems thinking	Limited integration of SE with cognitive and psychological models. Lack of application of ST to understand human decision-making processes in sustainability contexts.	(Blanchard et al., 1990:846; Watkins, 2000:266; Booher and Beaton, 2009:1319-1359)
Background of cognitive biases	Gaps in empirical studies explore how specific cognitive biases impact sustainability-related decision-making, particularly in industries transitioning to a CE.	(Petrie et al., 2024:121-127; Tversky and Kahneman, 1974:1124-1131; Gilovich et al., 2002:1-857; Morewedge et al., 2015:129-140)

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Overall, this literature review highlights the vital role of sustainable decision-making models in shaping a more sustainable and resilient future. The insights gained from the review provide a foundation for future research and practice, guiding decision-makers towards effective and impactful sustainable decision-making strategies.

This section comprehensively reviews existing models and theories, motivating the need for an integrated approach. It identifies gaps and establishes a foundation for the conceptual model development in Chapter 4.

Chapter 3, which follows, is positioned immediately after the Literature Survey and before the Conceptual Model chapter to serve several purposes. First, it creates a logical flow between the theoretical insights gained from the literature and the practical application of these insights in conceptual models. The Literature Survey chapter lays the groundwork by reviewing relevant theories, concepts, and existing models in sustainability, SE, ST, and cognitive biases. Building on this foundation, the Model Development chapter explains how these theoretical frameworks are operationalised into working models.

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3. Model and Framework Development

This chapter provides a detailed account of the development of the various models used in this research. The models play a crucial role in understanding the complex interactions within the CE and analysing cognitive biases' influence on decision-making processes. This chapter aims to systematically present the methodologies, theoretical foundations, and data used to develop each model and explain how these models are interlinked to provide a comprehensive framework for the research. Similar to how Gregor and Hevner (2013:337-356) explain the layout for DSR research. Each model section hereafter follows the design science research methodology, which is explained and visualised at the start of each section. These are all subcycles to the overall DSR method used for the thesis. This section fits into the DSR framework of the thesis, as shown in Figure 26.

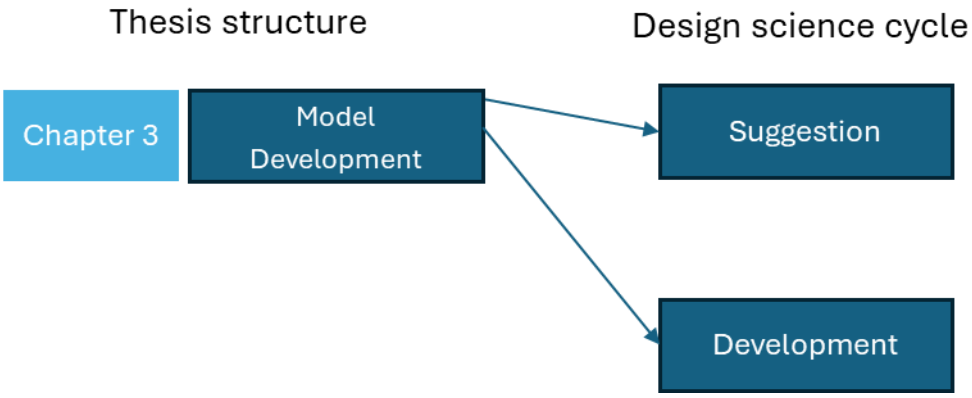

Figure 26. Design Science Research Framework - Chapter 3

3.1. Introduction

By developing a dedicated chapter for model development at this stage, three primary benefits are achieved:

- Enhanced clarity and depth: This chapter explains the modelling process, detailing the steps from theoretical conception to practical implementation. It offers readers a clear view of the assumptions, data sources, and methodologies used in developing each model, enhancing the research's transparency and robustness.
- Improved integration: Positioning this chapter between the literature review and the conceptual model chapters ensures a seamless transition from theoretical discussion to practical application. It allows for a more integrated approach, where the developed models are not just standalone entities but are linked to the broader theoretical context and the overall research objectives.
- Foundation for the conceptual model: The detailed exploration of each model's development provides a solid foundation for the subsequent Conceptual Model chapter. The models are synthesised and integrated to form a cohesive framework that addresses the research questions and objectives. By understanding the

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intricacies of each model's development, readers can better appreciate the logic and structure behind the conceptual model and its relevance to the research study.

The following sections will delve into the development of each model, beginning with an overview of the model development process and then providing a step-by-step description of how each model was constructed, validated, and integrated with the others.

3.2. Overview of Model and Framework Development Process

Figure 27 indicates the structure and framework of the following section. It provides an overview of the model development phases and the thesis's DSR approach. Some details are given here in the model development sections to ensure coherence. The reason for including model development in this section is to prevent sectional discussion of each model in the relevant sections.

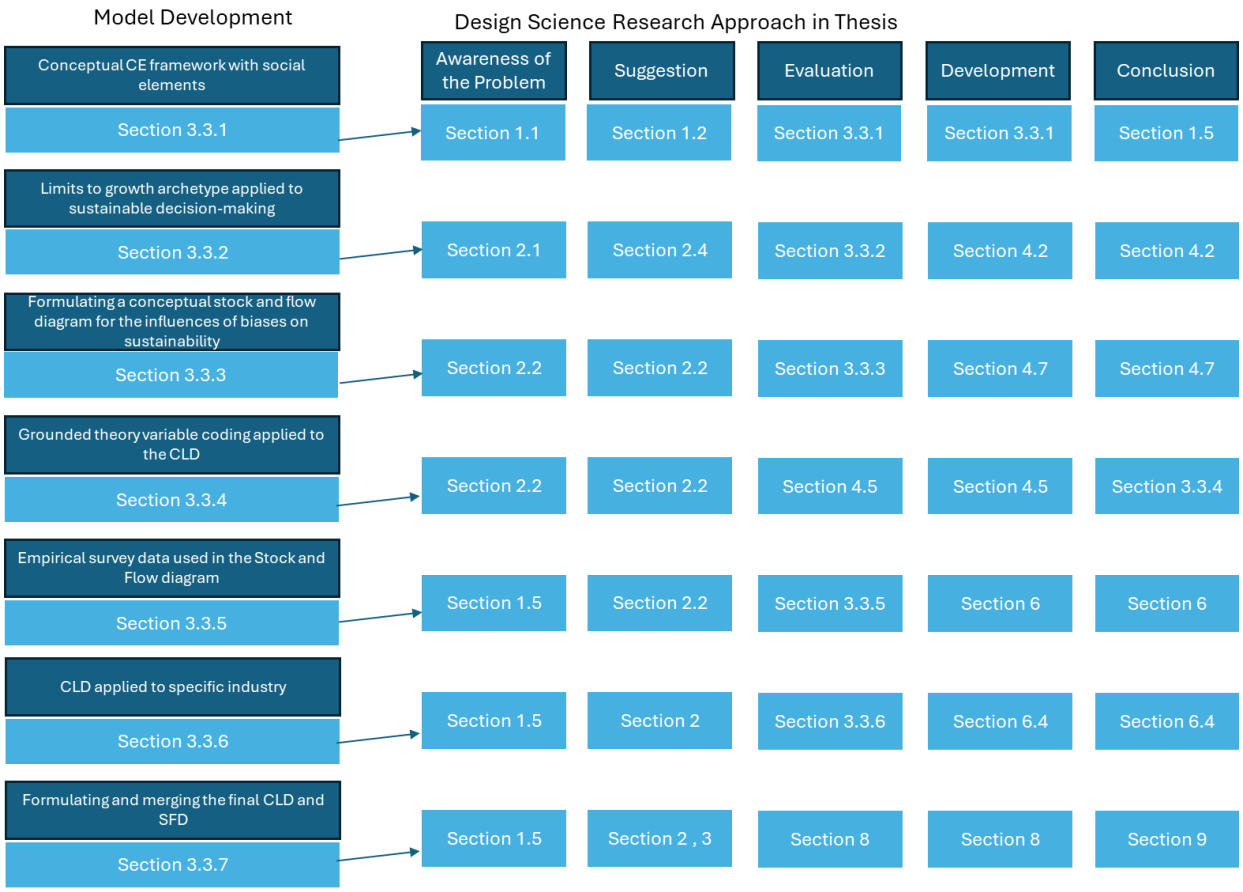

Figure 27. Structured Framework for Model Development

The following section discusses each model development phase in a sub-section. In addition to Section 5.3, the following Table 5 illustrates the research methodologies followed for each model development phase:

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Table 5. Research methodology discussion - Model development

Model development reference	Research methodology
3.3.1. Conceptual CE framework with social elements	A theoretical framework development approach was employed, utilising concept mapping and literature synthesis to conceptualise integrating social elements into the CE. This involved analysing existing CE models and identifying gaps related to social stakeholder roles.
3.3.2. Limits to growth archetype applied to sustainable decision-making	Applied systems dynamics modeling using the "Limits to Growth" archetype. This was achieved through causal loop diagramming and secondary data analysis from case studies to identify feedback loops that constrain or promote sustainable decision-making.
3.3.3. Formulating a conceptual stock and flow diagram for the influences of biases on sustainability	Employed systems thinking methodology to develop a conceptual stock and flow model. This involved iterative diagramming to visually map the stocks (accumulations) and flows (change rates) of cognitive biases influencing sustainability outcomes.
3.3.4. Grounded theory variable coding applied to the CLD	Utilised Grounded Theory methodology for qualitative coding of interview transcripts and literature. Thematic analysis was conducted to identify variables that were integrated into the CLD. This involved constant comparison to ensure the emerging themes reflected the data accurately.
3.3.5. Empirical survey data used in the Stock and Flow diagram	Conducted empirical research using a cross-sectional survey design. Quantitative data from stakeholders were collected via structured questionnaires and then statistically analysed using descriptive and inferential statistics to inform the stock and flow variables.
3.3.6. CLD applied to specific industry	A case study approach was adopted, where the causal loop diagram was contextualised within a specific industry. Data was collected through industry reports to tailor the CLD for industry relevance.
3.3.7. Formulating and merging the final CLD and SFD	Employed an integrative modelling approach to merge the final CLD and SFD. This involved iterative refinement and expert validation through stakeholder feedback and simulation testing to ensure the model's robustness.

3.3. Detailed Description of Model Development

3.3.1. Conceptual CE framework with social elements

The model development process in this section is integral to embedding a social pillar within the CE framework. The model draws upon SE principles and HSI, focusing on how human interaction affects systems performance. It aims to identify the key social elements that influence CE and integrate them within the existing technical and biological frameworks of CE.

Table 6. DSR summary for section vs thesis - Model Development 1

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration.	Problem identification and motivation. (In Section 1.5)

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Evaluation. Communication.	

Key questions driving the model development in Table 6 include:

- How can human interactions be effectively integrated into CE systems?
- What are the social impacts on the success of CE initiatives?

The research employed a qualitative research methodology. A semi-structured interview format was chosen for data collection, where industry specialists and stakeholders from CE and SE were interviewed. These interviews allowed for flexibility in exploring the subjective views of participants about how humans interact with CE systems. See Appendix E – Interview Information – Model Development 1. The model was initially developed as part of a master's study, laying the groundwork for understanding key dynamics within the system. While the initial focus was on specific elements, it provides a solid foundation for future model development, particularly in incorporating social aspects more comprehensively. By refining and expanding the model, it can offer deeper insights into the social elements and their interaction into the broader system.

Non-probability sampling was employed, targeting a small but relevant pool of experts in SE and CE. Given the study's exploratory nature, qualitative methods provided an in-depth understanding of the context surrounding the CE framework, especially the social aspects.

The overall research approach follows deductive reasoning, where existing theories on CE and human systems integration were used as a basis for formulating the conceptual model. This approach ensured the alignment of practical insights from the field with theoretical perspectives.

Data was collected using semi-structured interviews. These interviews were conducted with participants who are professionals and specialists in SE and CE from different geographical regions. Due to constraints such as the global COVID-19 pandemic, the interviews were carried out virtually.

Each interview focused on exploring how the participants perceived the role of human elements in CE frameworks, as well as how existing SE tools can be applied to improve the understanding and integration of human systems. Participants were asked about:

- The interaction of humans in the circular lifecycle.
- The social challenges are hindering CE adoption.
- Opportunities to enhance human-centric design in CE.

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The interviews were recorded and transcribed for subsequent thematic analysis. The thematic analysis method was employed to analyse the interview data. This approach enabled the identification of recurring themes and patterns related to human interactions in CE systems. ATLAS.ti software was used as a Computer-Aided Qualitative Data Analysis Software (CAQDAS), assisting in coding and categorising the themes. See Appendix F – Atlas.ti information – Model Development 1.

The data analysis followed the following process, shown in Figure 28:

Table A: Causal loop diagram process steps for themes explained

#	Process steps	Contribution	Result	Source of method
1	Evaluate data from interviewees individually	Review interview video recordings and read transcripts	Gain focus on specific themes from individuals	(Haynes et al., 2019:452-464)
2	Review literature study and research questions	Research proposal and draft thesis	Gain an understanding of data required	(Wang and Park, 2015:214-266)
3	Create code groups	Data from step 2 and ATLAS.ti word clouds	3 Code groups: Social/human/people Sustainability/CE Systems/modelling	(Tracy, 2020:219-225)
4	Code data according to discovered themes	Listed concepts and themes from step 1 and raw transcripts	Coding tree variables	Qualitative analysis
5	Iterate step 4 when new prominent themes are discovered	Coding tree variables from step 4	Broad coding tree variables	Qualitative analysis
6	Merge individual coded data to code groups	Combined codes from step 5 from all transcripts	Gain insight to the bigger system and repeating themes	(Auerbach and Silverstein, 2003:35-39)
7	Create network with relations	Code co-occurrence tables	Causal loop diagram with references to data	(Kenzie, 2021:179)
8	Iterate step 7 when new causal relationships are identified	Broad coding tree variables	Final causal loop diagram	(Eker and Zimmermann, 2016:4-10)

Table B: Causal loop diagram process steps for framework explained

#	Process steps	Contribution	Result	Source of method
1	Create codes for existing CE butterfly diagram	ATLAS.ti and (EMF, 2017b)	First code group	(Rambaree, 2014:2-9)
2	Identify social/human elements to be added to diagram	Interview transcripts and literature study	Second code group	(Silver and Lewins, 2010:326-334)
3	Grouping code group 2	Codes from step 2	Internal and external social elements grouped	
4	Linking code groups 1 and 2	Codes from steps 1 and 3	Connections between CE framework and social elements	Theme causal loop diagram from previous section
5	Iterate steps 2 to 4	Additional social elements identified through literature	Conceptual CE framework with social pillars	(Williamson et al., 2018:453-476)

Figure 28. Computer Aided Qualitative Data Analysis steps for HSI in the CE

Key themes that emerged from the interviews include:

- ST as a tool for embedding social elements into CE.
- The role of social responsibility and governance in enhancing the CE framework.
- Feedback loops that impact decision-making and system resilience.

Once the data was coded, the CLD was created to represent the relationships between these themes visually, as seen in Figure 29. This provided a structured way of understanding how human elements influence and are influenced by technical and biological elements in the CE.

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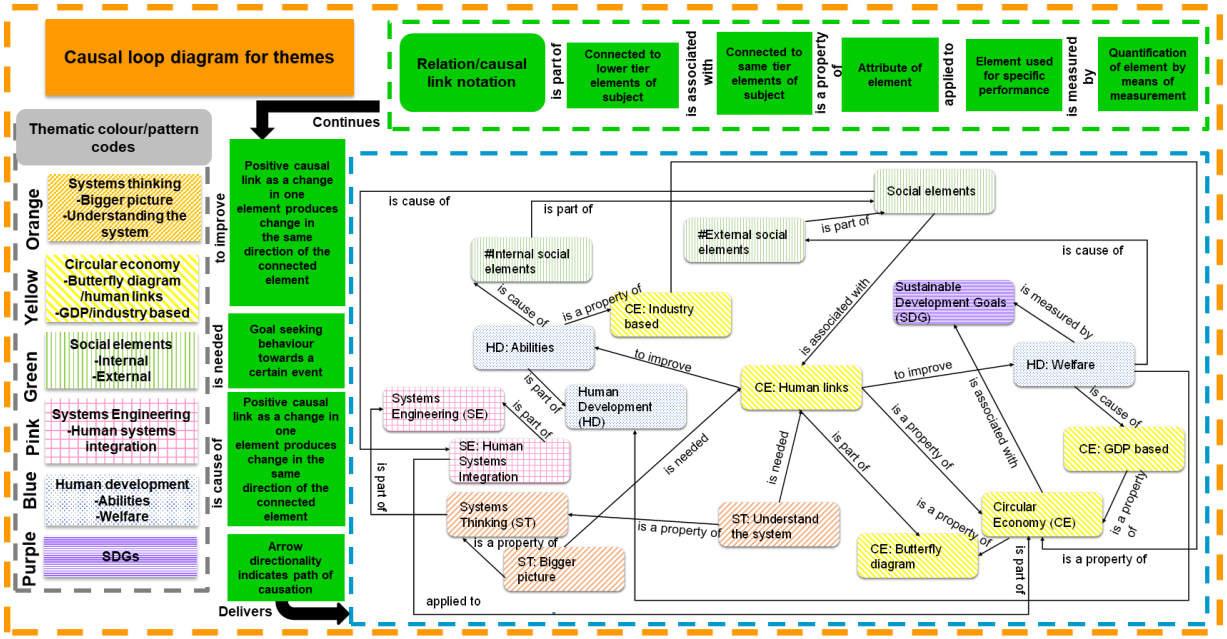

Figure 29. Theme causal loop diagram for HSI to the CE

The model development culminated in creating a Conceptual CE Framework, as seen in Figure 30 below, that incorporates social elements.

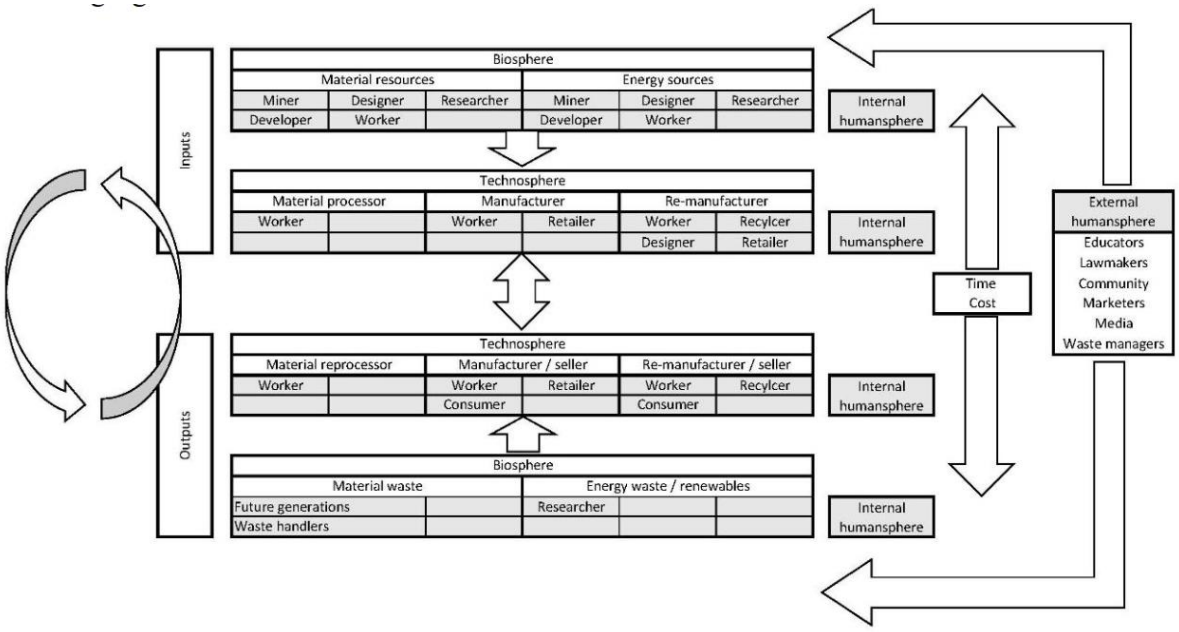

Figure 30. Theoretical, conceptual CE model with social elements

The framework builds on the butterfly diagram from the EMF shown in Figure 31, which is widely recognised as the technical backbone of CE.

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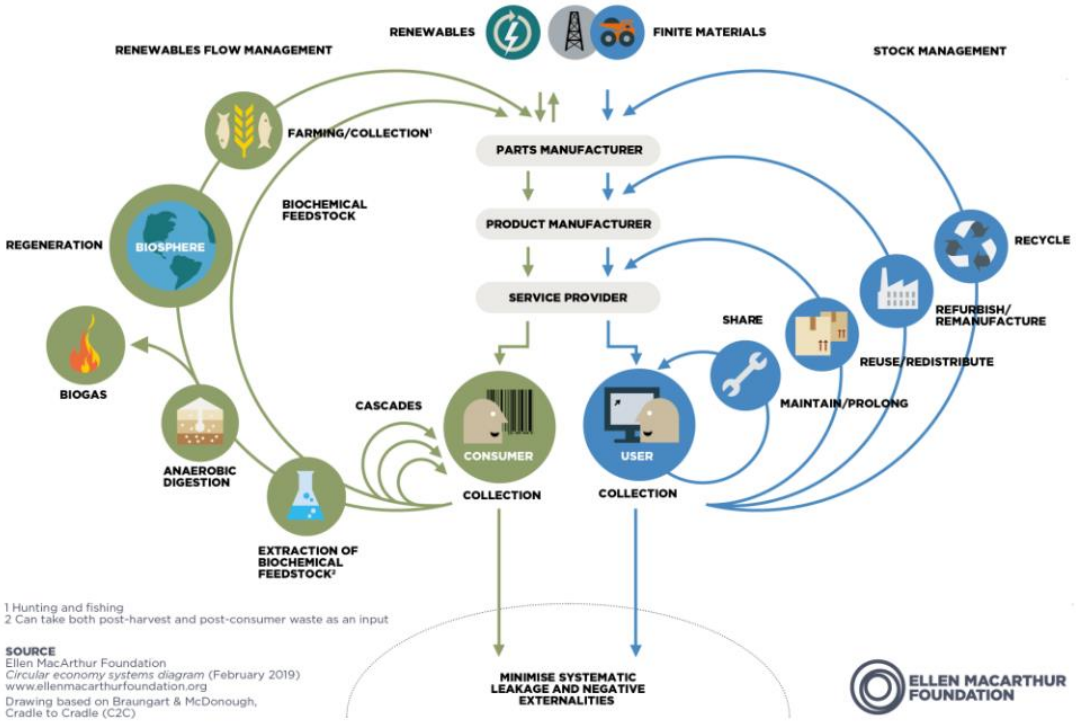

Figure 31. Butterfly diagram - Technical and biological cycles for the CE as per McDonough and Braungart (2002:202)

This section introduces social elements to the butterfly diagram to reflect internal and external human interactions with CE. Internal social elements include individuals directly involved in CE processes (e.g., workers, designers), while external social elements reflect societal influences (e.g., legislation, education), as seen in Figure 32.

The final CLD showcases how human involvement at different stages of the circular lifecycle (e.g., design, production, consumption, recycling) leads to systemic feedback and adjustments, emphasising the importance of transparency, inclusion, and responsible consumption.

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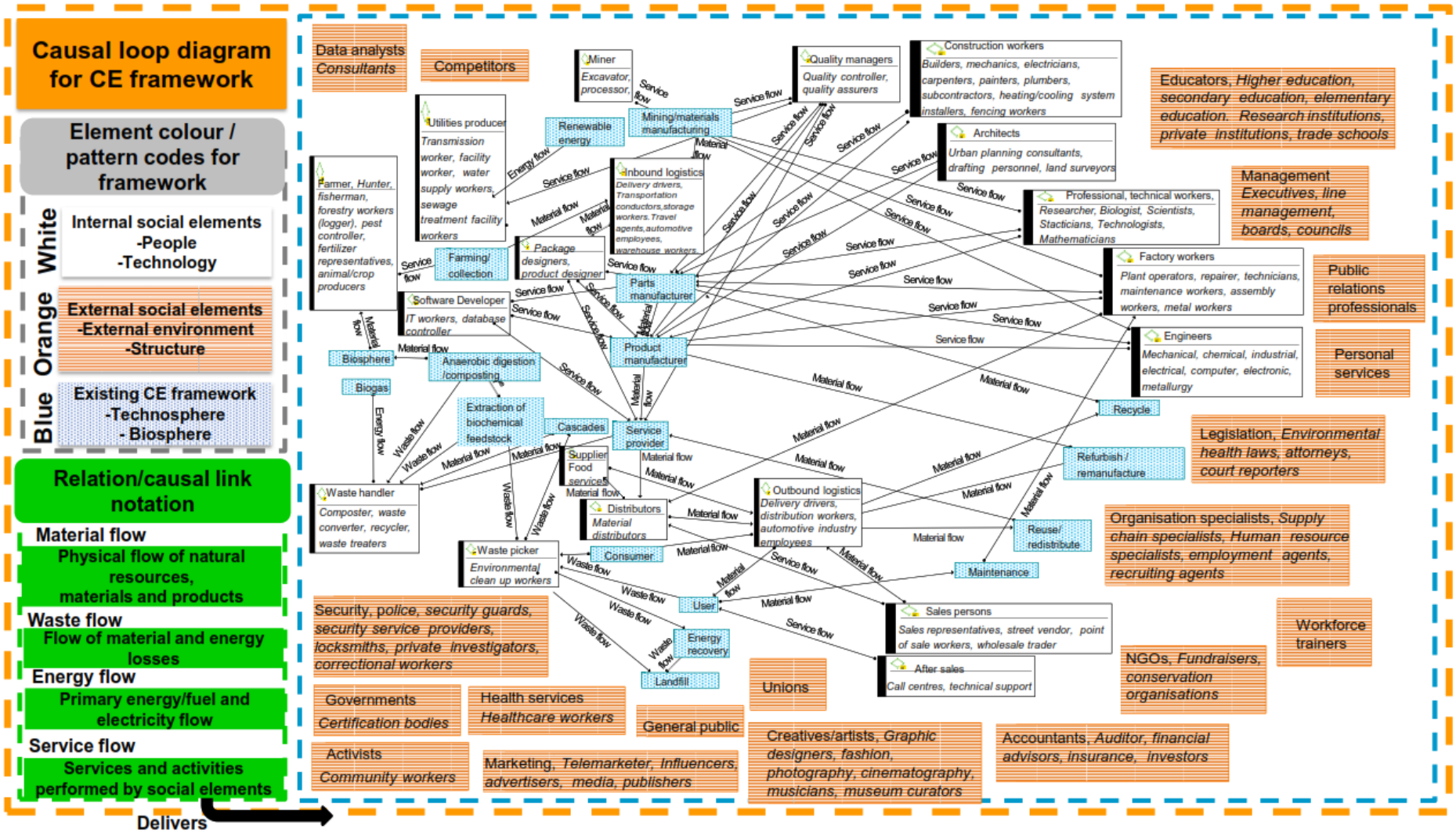

Figure 32. CE with HSI framework causal loop diagram

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To ensure the reliability of the developed model, a validation and verification process was conducted using the feedback from the interviewees and relevant literature. The model was iterated four times, incorporating suggestions from experts to refine the relationships between social and technical systems.

The following framework is a detailed CE framework with social elements, which is the final iteration of the HSI into the CE. This framework is also referenced in Figure 1, Section 1.5.

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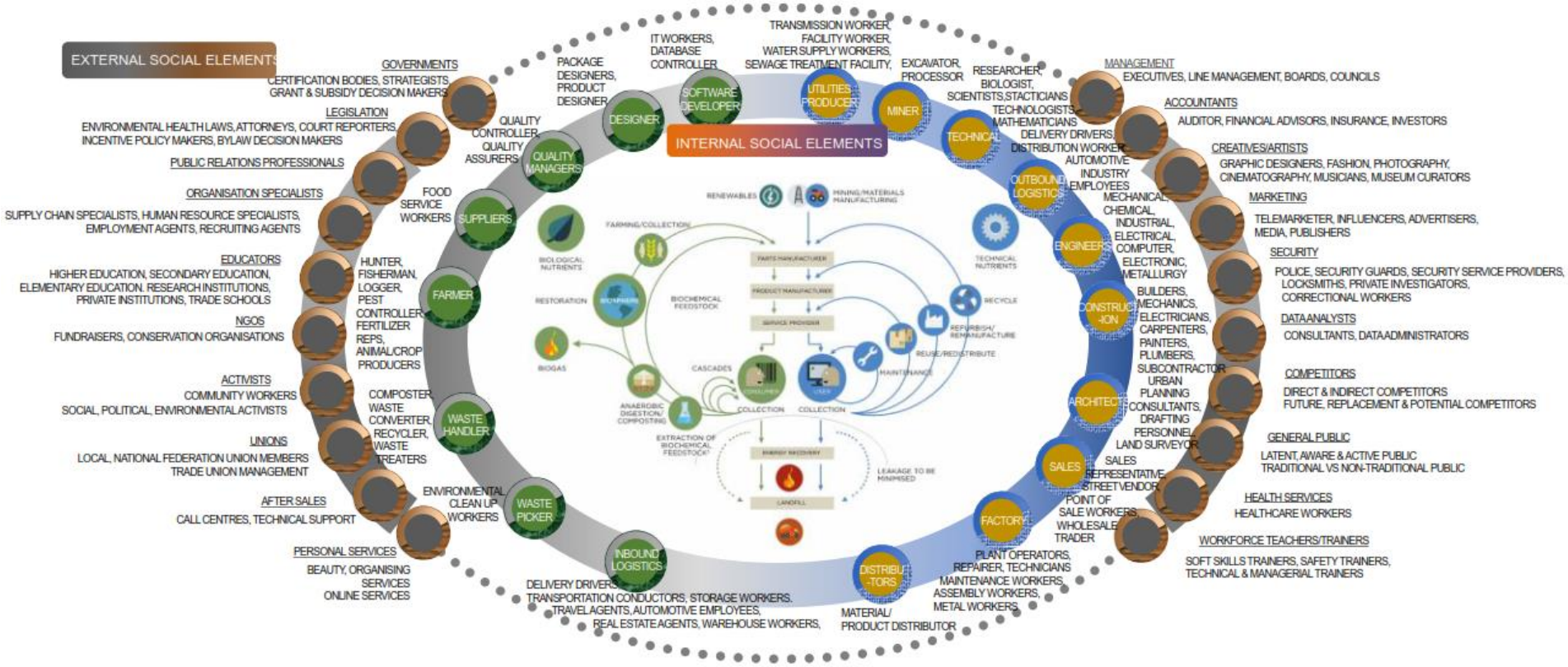

Figure 33. Detailed CE framework with social elements – Adapted from EMF (2017:1)

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Through this iterative process, the conceptual model was aligned with the SDGs, emphasising the social pillar's role in promoting long-term sustainability in CE practices. Validation was further supported by reviewing best practices from similar CE models to ensure the model's practical applicability.

The framework enables people to intentionally think outside of the silos and improve the welfare and abilities of those systems and the surrounding people.

Table 7. Contributions to theory, methodology and practice. Model development 1

	Contributions to		
Uses	**Theory**	**Methodology**	**Practice**
Description	Both the literature review and the data analyses contribute to the understanding of the relationships between people and the CE.	This research contributes to shift some focus to the social side of the CE. The perspective from the stakeholders' sides is crucial for implementing a successful transition from a LE to a CE.	The causal diagrams and conceptual framework show shareholders where they fit into the structure and what their roles and responsibilities are towards a more sustainable future.
Examples	The new framework can show research structures within the CE framework and how SE can be implemented within these structures.	This alternative view of human systems integration is valuable for system modellers in sustainable organisational data modelling and structuring. More precisely, the conceptual CE framework with social elements can be used for public presentation to understand the CE and for professionals implementing different methods to achieve a CE.	A use of these frameworks is for analysing the process of Knowledge and information management. With the people identified, the processes between them and the end goals, the information on sustainability could be better managed. Governing bodies can use this to address specific social aspects.

This framework introduces the concept of the human sphere within the CE and is currently used as an introduction to the thesis, as seen in Table 7. Further elements, such as decision-making and ST, will be applied to these concepts in the following models.

3.3.2. Limits to growth archetype applied to sustainable decision-making

The development of the model in this section aims to address the need to understand the influences of cognitive biases on decision-making within the CE. A systems approach is adopted to analyse stakeholder behaviour and biases that affect the performance of CE systems. The model centres on cognitive biases influencing decision-making, which are critical in optimising resource use and sustainability and ensuring effective circular flows in economic systems.

This section utilises system archetypes and SD modelling as foundational elements for developing a conceptual model. This model not only aids in understanding the complex interactions between various stakeholders but also provides a structured way to visualise the feedback loops affecting CE decisions, as seen in Table 8.

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Table 8. DSR summary for section vs thesis - Model Development 2

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration. Evaluation. Communication.	Define objectives for the solution. (In Section 2.4.3 and 4.2)

The model follows an inductive theory-building approach. It starts with an exploratory analysis of the literature on cognitive biases and decision-making frameworks within contexts of sustainability and CE. Principles from SE and ST support the methodology.

This approach explains the problem by mapping how cognitive biases interact with stakeholder behaviours in CE frameworks. The SSM is used to explore the problem space to capture different worldviews and perceptions of the stakeholders, as seen in Figure 34. This method is also discussed in Section 4.2.

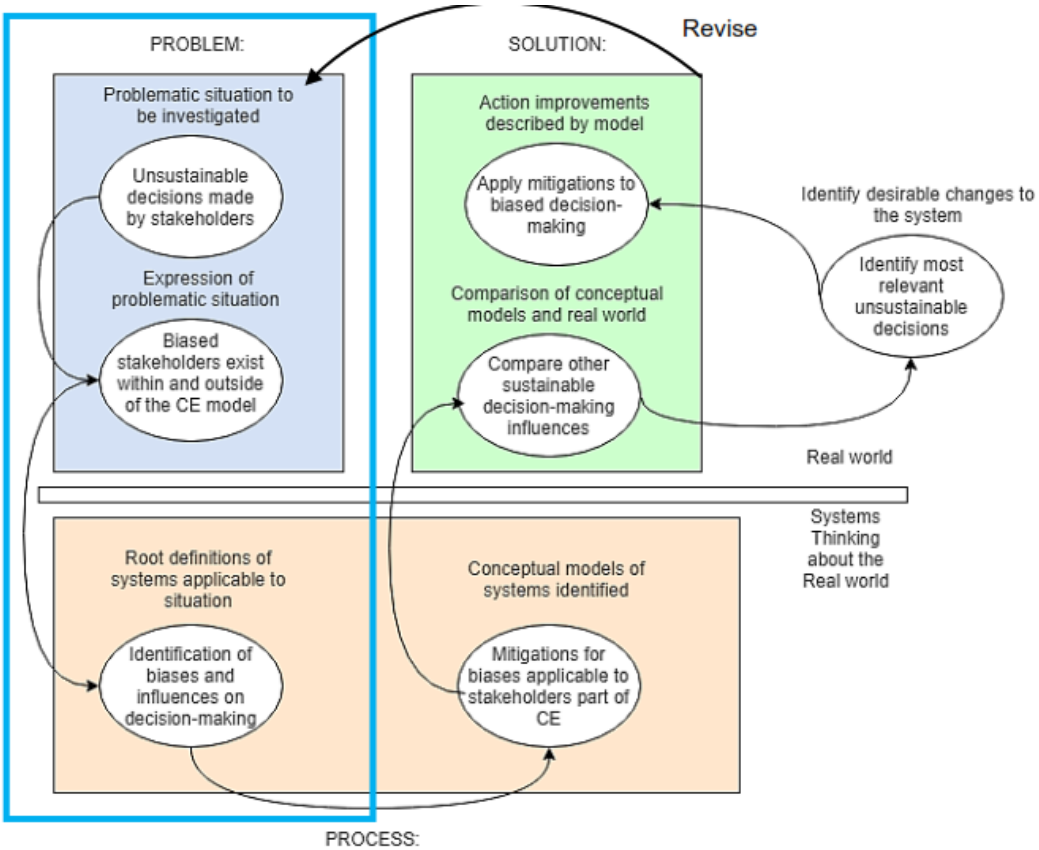

Figure 34. SSM applied to the problem of biased decision-making in the CE – Adapted from Sandfreni and Adikara (2020:1)

Key questions driving this section include:

- What are the cognitive biases that impact decision-making in the CE?

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- How can systems modelling and archetypes be used to mitigate unsustainable decisions?

The research methodology further incorporates tools such as Bayesian causal modelling and decision-making frameworks like the OODA loop (Observe, Orient, Decide, Act) and Recognition Primed Decision (RPD) models. These are instrumental in understanding how biases develop and influence decisions in complex systems, as seen in Figure 35.

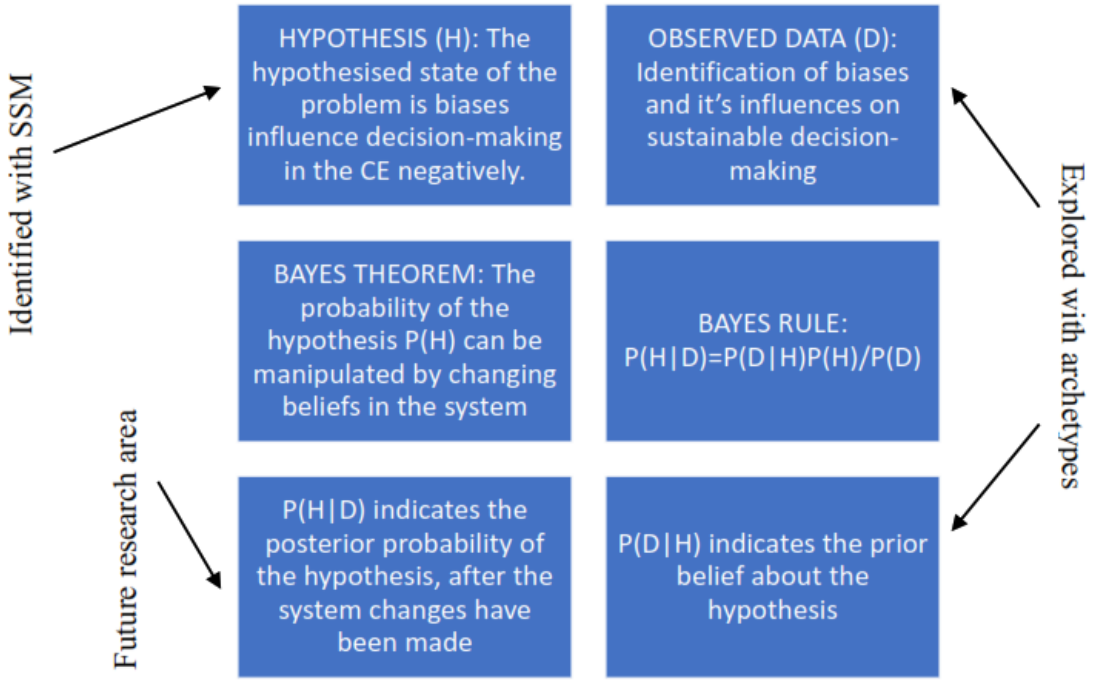

Figure 35. Bayes theorem applied to Model Development 2 – Adapted from Fenton and Neil (2011:10-21)

The data collection process for this model is primarily qualitative, utilising both literature review and case studies. The literature review focuses on understanding previous research on decision-making frameworks, biases, and sustainability models. These studies provide a theoretical grounding for model development, as seen in Figure 36.

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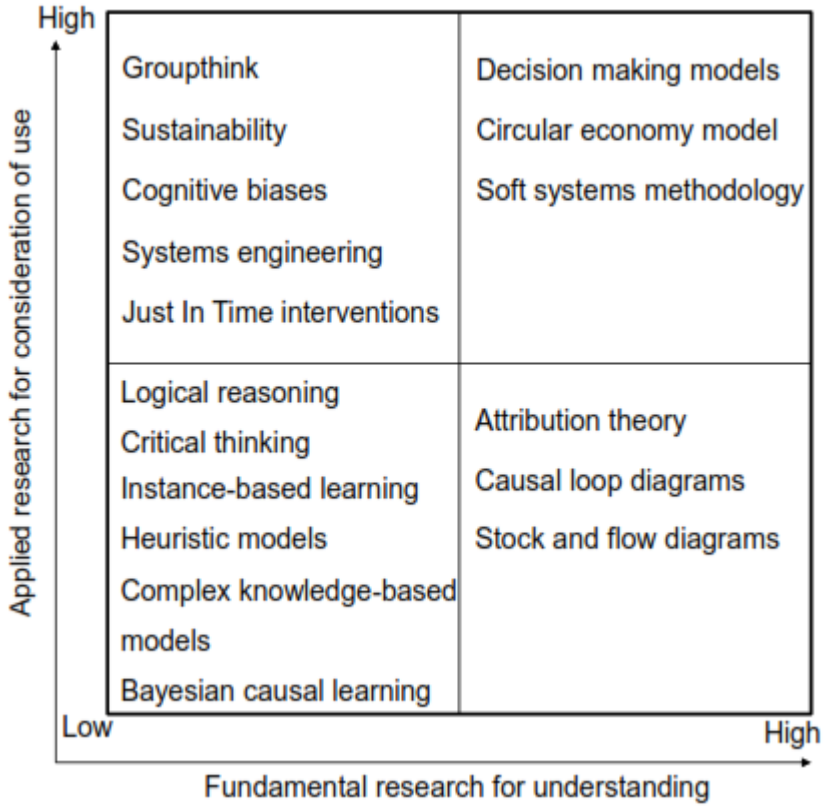

Figure 36. Research orientation Quadrant model – Adapted from (Klímová and Zitek, 2017:36-48)

Data analysis was supported by ST tools such as CLDs. The results of systems modelling allowed the identification of key leverage points in the system where cognitive biases could be addressed to improve decision-making within the CE. The conceptual model formulated in this study builds on the LtG system archetype. The LtG archetype in Figure 37 describes how reinforcing growth processes are balanced by limiting factors, which in the context of CE are cognitive biases that prevent sustainable decision-making.

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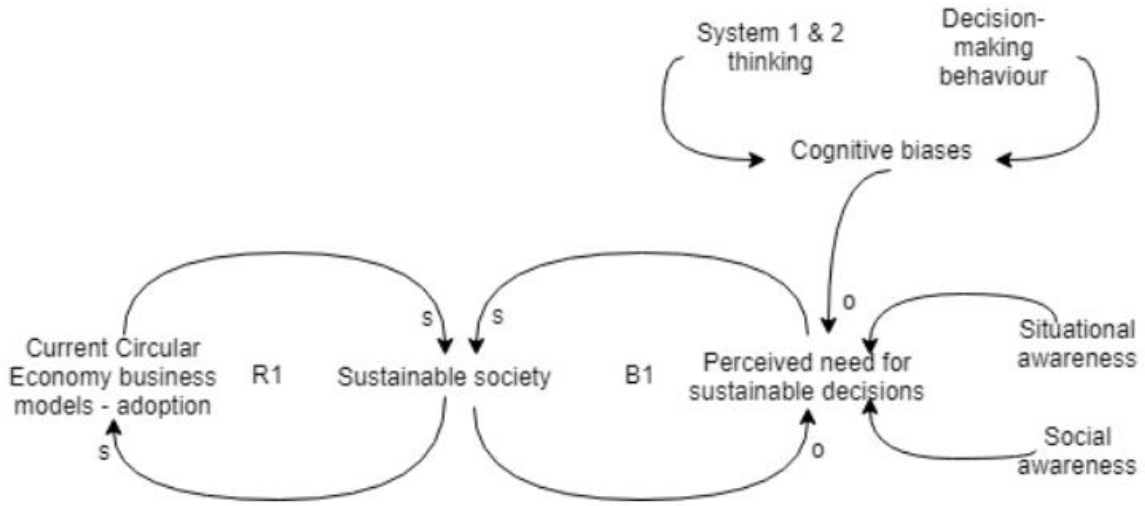

Figure 37. Limits to Growth archetype applied to sustainable decision-making.

The model developed has the following key components:

- Reinforcing Loop: This represents the positive feedback cycle where adopting CE principles leads to a more sustainable society. As sustainability practices improve, they reinforce stakeholder buy-in, strengthening the CE framework.
- Balancing Loop: The balancing loop represents the limiting effects of cognitive biases. These biases, such as overconfidence or status quo bias, restrict the effectiveness of sustainability efforts and create resistance to change. In this loop, the need for sustainable decisions may decrease as biases undermine long-term strategic goals.

The decision-making loop incorporated into the model helps explain how stakeholders ascend from unconscious biases to more rational and informed decision-making processes. The model facilitates improved outcomes by systematically addressing cognitive biases at various decision-making stages.

The model also integrates elements of Bayesian reasoning, where prior beliefs (biases) are updated based on observed data and changes in SD.

A validation and verification process ensured the conceptual model's robustness. The following steps were included:

- The model was presented to domain experts in CE and ST for feedback. This helped refine the model by incorporating practical insights and addressing any gaps identified by the experts.

The final iteration of the model serves as a decision-support tool, enabling stakeholders in the CE to visualise the long-term impacts of their decisions and reduce the influence of cognitive biases. From this CLD, an SFD can now be developed, as seen in the following section.

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3.3.3. Formulating a conceptual stock and flow diagram for the influences of biases on sustainability

The development of SD models in this section is guided by the necessity to explore how behavioural biases influence decision-making within the CE. SD has long been recognised as a powerful tool for analysing complex STS by mapping feedback loops and interrelations between variables. This section focuses on integrating biases and mental models into the SD framework to understand their effects on sustainable decisions in the CE. The model development process, thus, seeks to provide both qualitative and quantitative insights into how such biases shape societal trends toward or away from sustainability.

Table 9. DSR summary for section vs thesis - Model Development 3

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration. Evaluation. Communication.	Design and development of the artefact. (In Section 4.7)

The core question driving the model's development in Table 9 is: "Where do cognitive biases fit into sustainable decision-making?" This question aligns with the broader goal of SD modelling—to reveal hidden structures in complex systems, particularly how feedback loops either reinforce or balance the pursuit of sustainability. The model seeks to answer this question by identifying key variables, such as mental models and supporting cognitive biases, that drive decision-making in a socio-economic context.

The methodology utilises a mixed-methods SD approach, combining CLD and SFD to map out and simulate the dynamic behaviours within the CE. A CLD is first developed to qualitatively capture relationships between social, economic, and environmental variables. The diagrams in Figure 38 provide a visual framework to represent reinforcing and balancing loops, particularly those impacted by cognitive biases and mental models. The CLD presented was created with Vensim software.

The main two loops in the centre of the diagram indicate the following from the left:

- An increased adoption rate of CE models and approaches will increase the sustainable development of society. This will, in turn, increase both corporate social responsibility and the standard of life (Trainer and Alexander, 2019:247-60; ElAlfy et al., 2020:5544). The reinforcing loop is completed with a return of improved adoption rates through a more sustainable society.
- The balancing loop is presented with the improved sustainable society not perceiving the need to make sustainable decisions any more than what is currently

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done. The loop is completed with growth in sustainable decisions that lead to better sustainable development. All of these are impacted by biases (supportive or opposed) and mental models.

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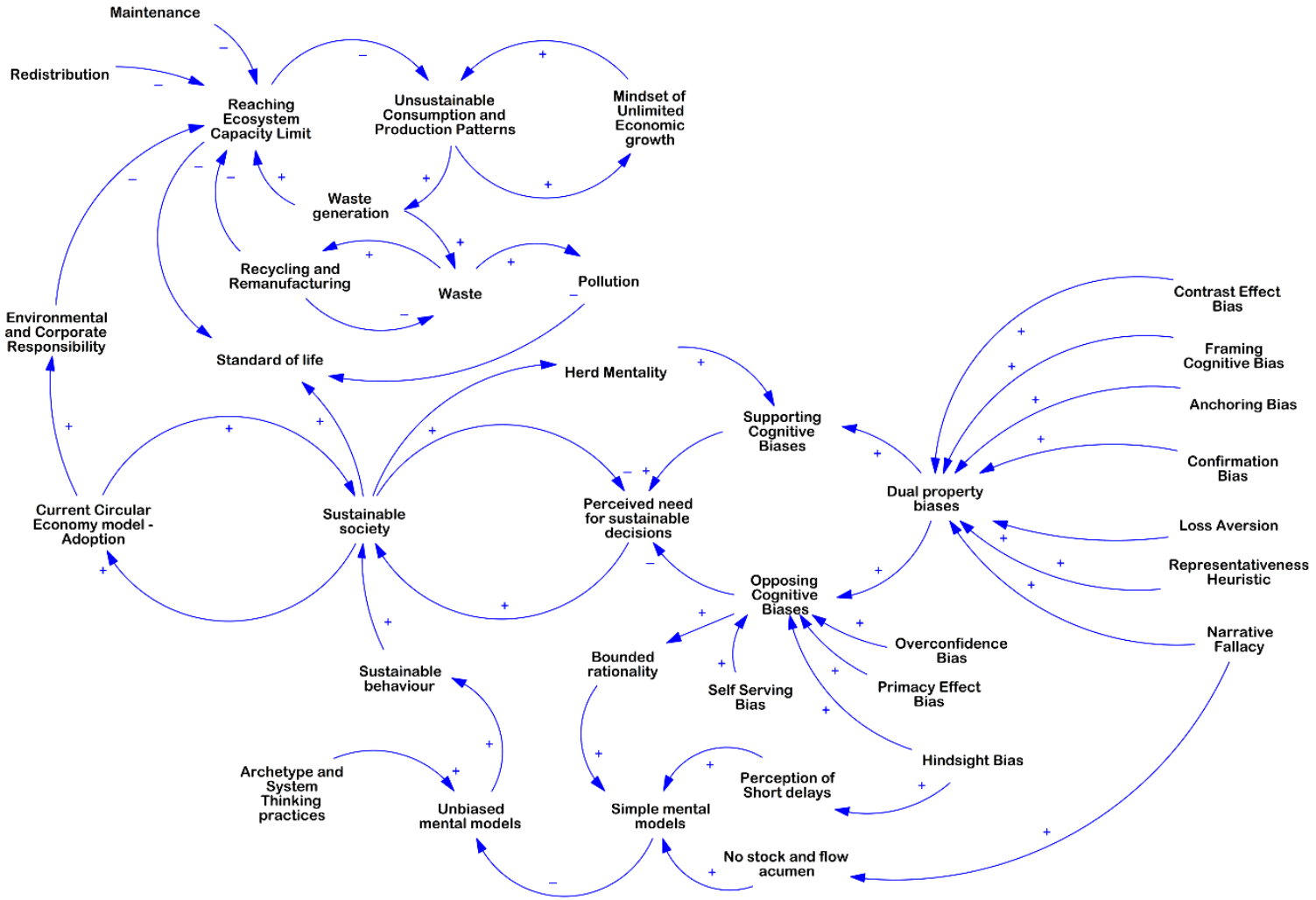

Figure 38. The causal interpretation presented through a CLD for the conceptual integration of critical biases into the CE phases

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Given the qualitative nature of many factors involved, the data-gathering process focused on reviewing existing literature and empirical studies that discussed the behavioural dimensions of sustainability and the CE. Key variables such as cognitive biases, moral intensity, and decision-making processes were extracted from these sources and mapped into the SD models (Lane, 2004:433). While "Reaching Ecosystem Capacity Limit" does contribute to sustainability awareness, the relationship is already embedded in the system through waste generation, herd mentality, corporate responsibility, and cognitive biases. A direct arrow would oversimplify these interactions, missing the critical role of perception, social influence, and bias in sustainability decision-making.

For example, this model drew on well-established concepts from behavioural psychology, including dual-process theories of reasoning and risk perception (Prentice, 2004:55-72). All these concepts can be seen in Table 10 below.

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Table 10. Variables and data items – Model Development 3

Variable name	Enabler or Barrier	Internal or External	Political, social or Legal	Delay	Sources
Cognitive biases	Both	Internal	Social and political	Delay	(Michael Shayne et al., 2007)
Social norms	Both	External	Social and political	Delay	(Gifford and Nilsson, 2014:141-157)
Moral intensity	Enabler	Internal	Social	Delay	(Bastons and Armengou, 2017:969-987)
Risk perception (Risk aversion)	Barrier	Internal	Social and legal		(Ford and Richardson, 1994:205-221)
Decision-making	Both	Internal	Social		(Klein et al., 1989:462-472)
Ethical behaviour	Both	Internal	Social and legal	Delay	(Inigo and Blok, 2019:280-291)
Systems thinking	Enabler	Internal	Social	Delay	(Kopnina, 2019:1-15)
Dual process models	Enabler	Internal	Social	Delay	(Evans, 2003:454-459)
System 1 and 2 thinking	Enabler	Internal	Social	Delay	(Morewedge and Kahneman, 2010:435-440)
Environmental responsibility	Enabler	Internal	Social and legal	Delay	(Haleem et al., 2022:1967)
Corporate responsibility	Enabler	External	Social and legal	Delay	(Grigore et al., 2021:763-782)
LCA, EoL and MFA [a]	Enabler	External	All three	Delay	(Pinto, 2019:1-21)
SDGs	Enabler	External	Political		(Arora and Mishra, 2019:339-342)
CE	Enabler	External	Social and political		(Schröder et al., 2020:1-9)
Energy frameworks	Enabler	External	Political and legal		(Devins and Medsker, 1982)
Material frameworks	Enabler	External	Political and legal		(Wiedmann et al., 2015:6271)
Doughnut economy	Enabler	External	Social and political	Delay	(Krauss, 2018:452-457)
GDP per capita		External	Social and political		(Sverko Grdic et al., 2020:3060)
Waste generation per capita	Barrier	Internal	Social and political		
Recycling	Enabler	Internal	Social and political		
Remanufacturing	Enabler	Internal	All three		(Bittar, 2018:527-536)
Redistribute	Enabler	Internal	All three		(Milios, 2018:861-878)
Maintenance	Enabler	Internal	All three		(Schulze Spüntrup et al., 2021:4-28)
Industries	Barrier	External	All three	Delay	(Sassanelli et al., 2019:440-453)

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-Automotive -Food -Construction -Steel -Power production -Textiles -Petrochemical -Medical		Internal	All three	Delay	
Demographics	Both	Internal	Social		(Ford and Richardson, 1994:205-221)
Income	Both	Internal	Social		
Education	Both	Internal	Social		
Situational determinants	Barrier	External	All three		(Belk, 1975:157-164)
Sustainable actions	Enabler	Internal	All three	Delay	(Triantafyllidou and Zabaniotou, 2022:113-139)
Sustainable decisions	Enabler	Internal	All three	Delay	
Mental models	Both	Internal	Social	Delay	(Watkins, 2000:266)
Archetypes	Enabler	External	Social	Delay	(Kim, 1992:2-30)
Bounded rationality	Enabler	Internal	Social	Delay	(Bolis et al., 2017:310-322)
Perceived situation	Barrier	External	Social and political		(Lane and Rouwette, 2022)
Real-world	Barrier	External	All three		

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Once key feedback loops were identified, the study proceeded to build SFDs, which quantitatively simulate the impact of these variables over time. These models were constructed and validated using the Vensim software, a widely used tool for SD modelling. The primary focus is identifying leverage points where small changes in cognitive biases could lead to significant shifts in sustainable behaviour, as revealed by simulation outputs showing stock and flow dynamics over time.

The SFD, in Figure 39, is built to simulate these relationships quantitatively. It provided insights into how societal perceptions and needs for sustainability evolve over time, affected by the prevalence of supporting versus opposing biases. The model was validated through sensitivity analysis, where different values of cognitive biases were tested to see how they impacted the system's behaviour over time. The SFD is constructed by identifying and modelling all the interactions shown in Figure 38.

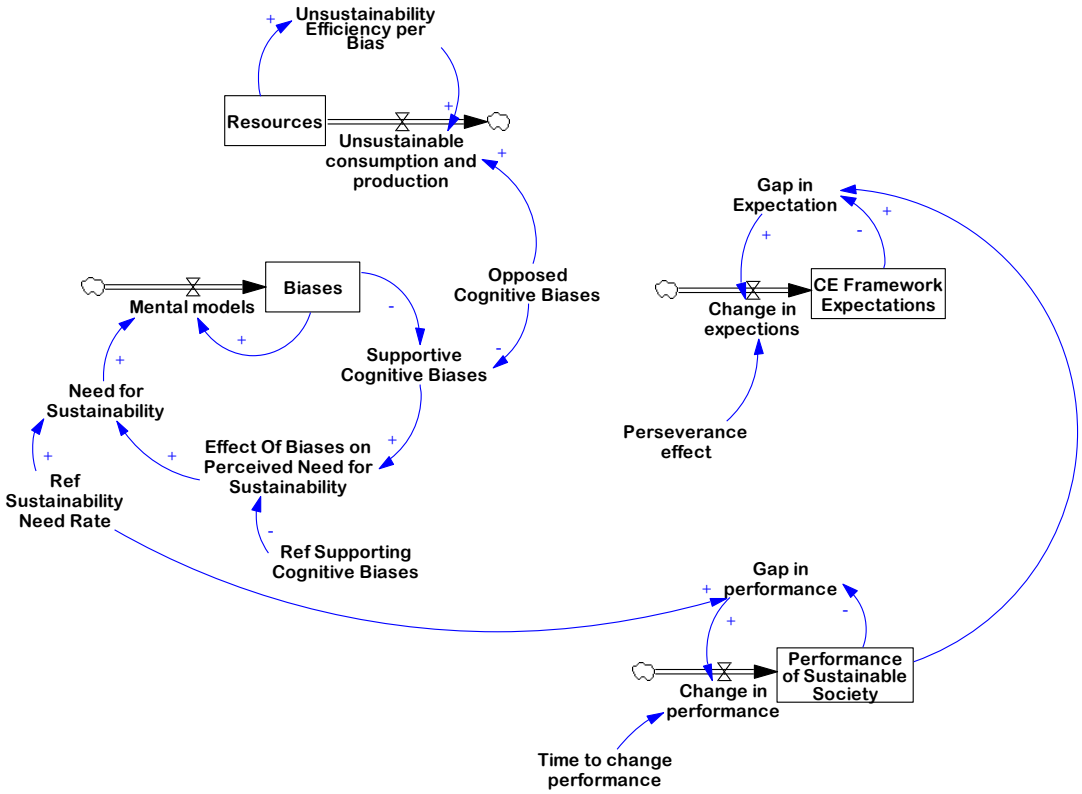

Figure 39. Formulating a conceptual stock and flow diagram for the influence of biases on sustainability - Model Development 3

The SFD is simplified first to fit the LtG archetype for simulation in this section, as seen in Figure 40.

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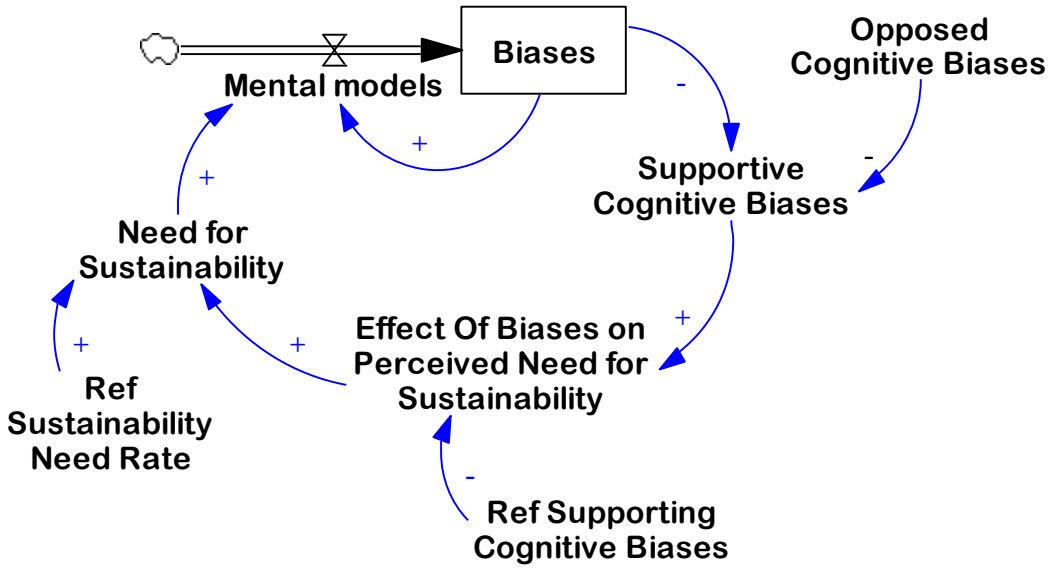

Figure 40. A "limits to growth" stock and flow diagram of the bias influences on sustainability

The model was validated through sensitivity analysis, where different values of cognitive biases were tested to see how they impacted the system's behaviour over time. The simulation details can be seen in Section 4.7 as part of the conceptual model development for the overall thesis. The simulation results, including limits-to-growth curves, show how supporting cognitive biases could transform simple mental models into more sustainable models. While the model provided valuable insights, it is also acknowledged that the availability of more quantitative data would allow for further refinement and validation of the model, which can be seen in the following sections and models.

This section's model contributes to the growing body of literature on SD and behavioural research by integrating cognitive biases into the modelling of CE systems. The development of these SD models offers a novel way to simulate and analyse the influence of human behaviour on sustainability outcomes. It highlights the importance of addressing both reinforcing and balancing loops in promoting sustainable development. By focusing on mental models and cognitive biases, the model adds a behavioural dimension to SD that is often overlooked in traditional economic and environmental models. The detailed model and results are discussed further in 3.3.5.

3.3.4. Grounded theory variable coding applied to the CLD

This section focuses on validating the model from the previous section in Figure 38 to investigate the impact of cognitive biases on decision-making within the CE. The CE framework aims to decouple economic growth from resource consumption by creating closed-loop systems of resource use. However, cognitive biases can hinder the adoption of sustainable decisions within this framework. Behavioural SD, by combining

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ST with behavioural science, provides a means to analyse and model the complex interactions between human decisions and systemic outcomes. Grounded theory, a qualitative research method, is employed in this study to validate the relationships between variables in the CLD that represent the dynamics of decision-making within the CE.

Table 11. DSR summary for section vs thesis - Model Development 4

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration. Evaluation. Communication.	Evaluation. (In Section 4.5)

The main question guiding this model development in Table 11 is: “How do cognitive biases influence decision-making in the context of the Circular Economy?” This question underpins the design of a CLD that captures the feedback loops between supporting and opposing cognitive biases and how they influence the adoption of sustainable behaviours. By addressing this question, the model seeks to uncover leverage points where small changes in decision-making can lead to more sustainable outcomes within the CE. Moreover, understanding the role of biases in decision-making processes enables stakeholders to mitigate negative influences and encourage behaviours that align with sustainability goals.

The research employs grounded theory as the primary methodological approach to validate the behavioural SD model. Grounded theory involves the systematic review of literature to identify and categorise key variables, relationships, and causal effects. This methodology analyses existing literature to assess the strength and direction of causal relationships between variables in the CLD. The grounded theory approach is particularly useful for this study, as it allows the iterative refinement of the model based on empirical evidence extracted from literature. The development process is structured in phases: literature review, data coding, and causal relationship validation , as can be seen in Section 4.5. The iterative process of refining the model involves reviewing existing studies on CE and decision-making frameworks. Once key variables are identified, the CLD is evaluated, which serves as the foundation for validating causal links through literature analysis.

The software Atlas.ti is used to capture all the codes, themes and connections, as seen in Appendix G – Model Development 4 – Atlas.ti screenshots. Focused coding was used to refine and consolidate these categories, leading to the identification of core causal loops that drive sustainable decision-making in the CE.

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The results were used to refine the CLD, ensuring that it accurately and appropriately reflected the empirical evidence found in the literature. All the validated loops can be seen in Figure 41. For example loops A to A1 was validated through code connections between CE to ECR.

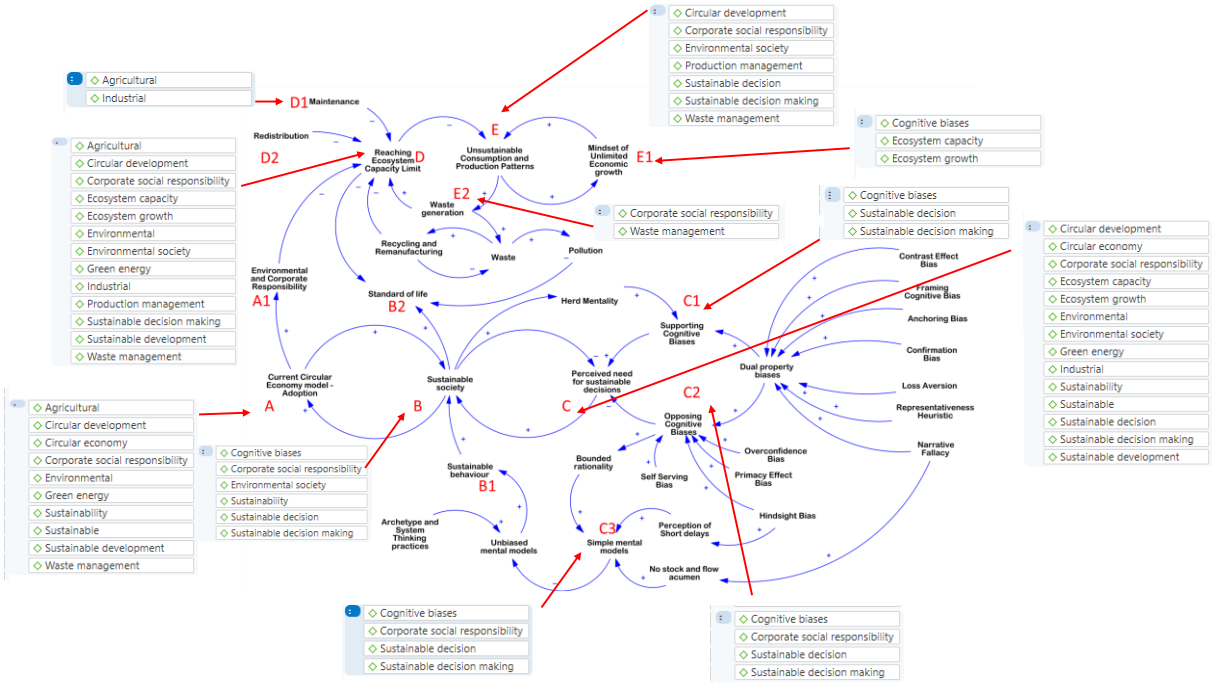

Figure 41. Variable coding added to the CLD - Model Development 4

The validated CLD provides a comprehensive framework for understanding how human behaviour influences the success or failure of sustainability initiatives within the CE. Moreover, the use of grounded theory in model validation ensures that the causal relationships identified in the model are grounded in empirical evidence, making the model a valuable tool for future research and practical applications. After the CLD is validated, the SFD created from it can now be simulated with real data, as seen in the next section.

3.3.5. Empirical survey data used in the Stock and Flow diagram

This section's model aims to promote sustainability by closing the loop of resource usage and waste management. However, decision-makers, including consumers, businesses, and policymakers, are often influenced by cognitive biases that can obstruct the adoption of sustainable practices.

This model integrates cognitive biases into an SD model, using both qualitative and quantitative data to simulate how these biases shape decisions within the CE. By modelling these biases, the aim is to provide a more nuanced understanding of the dynamics that underpin stakeholder behaviours in the CE.

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Table 12. DSR summary for section vs thesis - Model Development 5

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration. Evaluation. Communication.	Demonstration. (Seen in Section 6)

The model in Table 12 specifically explores how biases such as confirmation bias, anchoring bias, and status quo bias, among others, shape mental models of sustainability. The focus is on identifying where these biases create barriers to sustainable decision-making and determining leverage points for intervention.

The BSD model integrates both empirical survey data and SD to explore the biases impacting CE decision-making. A survey was carefully designed to capture the behaviours, perceptions, and biases of stakeholders involved in the CE. See Appendix H – Model Development 5. More detail on this process can be found in Section 6. The survey responses were coded and categorised to identify recurring themes and patterns that reflect cognitive biases. The data gathered were then integrated into the SD model. These diagrams map the relationships between variables such as cognitive biases, decision-making, and sustainability outcomes, providing a clear structure for further analysis.

Data were collected through a structured survey designed to assess CE stakeholders' decision-making processes. Stakeholders included consumers, businesses, and policymakers who play a role in the sustainability landscape. The survey consisted of 26 questions, with 18 specifically selected for this section's simulation. The questions aimed to uncover cognitive biases by exploring decision-making drivers, risk perceptions, and the sources of information stakeholders rely on. Survey responses were analysed using Atlas.ti, which facilitated the coding and categorising of biases and sustainability-related behaviours. The data collection process also involved refining the survey through pilot testing to ensure its validity and reliability. See Appendix B – Survey questions extracted from Jotform and Appendix C – Raw data from surveys.

The diagram from Figure 40 is then simulated with the results from the Atlas.ti analysis of the survey questions. All of this is demonstrated in Section 6. The following information is in Table 13:

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Table 13. Variable and simulation details for conceptual SFD with survey results

Variable/simulation setting	Value (BaseCase)	Value (HigherCap)	Value (LowerOpp)
Biases stock	201 (all the initial opposing biases)	No change	100
Opposed Cognitive Biases	1015 (the total biases at play)	2030	No change
Reference sustainability need rate	0.134 (focus and informed sustainability awareness)	No change	No change
Reference supporting cognitive biases	0.80 (the ratio of the total bias to the total supportive bias count)	No change	No change
Step increment	0.25	No change	No change
Initial value increment	0.00	No change	No change
Final value increment	100.0	No change	No change

The model is also validated through a sensitivity analysis in Chapter 7.3, testing how variations in cognitive biases affect decision-making and sustainability outcomes. Different scenarios were simulated, ranging from a high presence of opposing biases to a strong dominance of supportive biases. The results were compared to real-world data and previous studies on sustainability behaviour to ensure the model's reliability.

This simulation is particularly valuable for policymakers and practitioners seeking to promote more sustainable societal behaviours. The model also opens avenues for further exploration, particularly in developing interventions that mitigate the impact of opposing biases and enhance supportive ones.

The next section describes the application methodology followed to test this model in a real-world application.

3.3.6. CLD applied to specific industry

This section explores the interplay between Sustainable Technology Management Initiatives and Circular Economy Model Adoption, and the integration of AI within these frameworks. The goal is to develop a system dynamic model that maps out the critical feedback loops, stakeholder dynamics, and biases influencing sustainable decision-making within a CE.

Central to this section is the modification of Figure 38, which serves as the foundation for modelling how these elements interact.

The CLD enables stakeholders to visualise the interdependencies between various socio-economic and environmental variables, which are central to sustainable practices.

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Table 14. DSR summary for section vs thesis - Model Development 6

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration. Evaluation. Communication.	Demonstration. (In Section 6.4.4)

The key question that guides the development of the model in Table 14 is: “How do the dynamics between Sustainable Technology Management, CE adoption, and AI integration shape sustainable decision-making and system behaviour in the CE?”

This question is motivated by the need to understand how biases, technological innovations, and decision-making frameworks interact within CE models. Understanding these dynamics is crucial for predicting how changes in one part of the system affect the whole, providing actionable insights for policy and decision-making.

This model development utilises a mixed-method approach, integrating qualitative and quantitative methods to capture the complex feedback loops within sustainable technology management and CE adoption. Through qualitative literature review from Sections 1 and 2 and focus group discussions, preliminary CLDs are constructed to outline the system map. Quantitative methods, in the form of simulation models, are then applied to test the dynamics of the model and predict future behaviour. This iterative process, involving constant refinement and testing, ensures a robust model that accurately reflects real-world dynamics.

A deductive approach was used to evaluate existing theoretical frameworks, while an inductive approach allowed for identifying new patterns that emerged from the data. The core of the model is the CLD in Figure 42, which maps out the interactions between key variables. The diagram includes both reinforcing and balancing loops, capturing the dynamic nature of decision-making in a CE.

Reinforcing loops demonstrate how increasing the adoption rate of CE models leads to greater societal sustainability, which in turn enhances corporate social responsibility and the standard of living.

Balancing loops highlight how improvements in sustainability can reduce the perceived need for further action, potentially leading to stagnation in decision-making.
These loops are influenced by cognitive biases such as risk perception, sunk cost fallacy, and status quo bias, which shape how decisions are made in response to new information.

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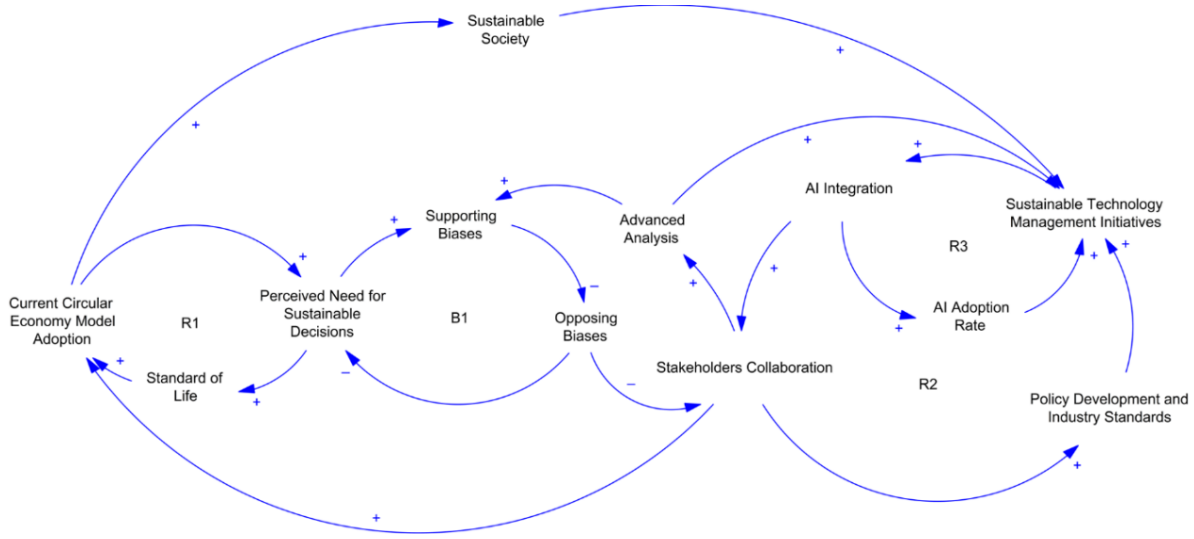

Figure 42. CLD indicating literature theme causes-and-effects - Model Development 6

Expert reviews and peer feedback were incorporated to refine the model and ensure its relevance to real-world CE practices. Triangulation methods involving multiple data sources enhanced the reliability and validity of the model.

By mapping these biases and their influence on system behaviour, this model provides valuable insights for policymakers and businesses seeking to promote sustainability in an increasingly complex world.

3.3.7. Formulating and merging the final CLD and SFD

The core objective is to explore how cognitive biases impact stakeholders' choices and identify leverage points for interventions promoting sustainable practices across various industries.

In addressing this challenge, this model development is underpinned by several key questions: How do cognitive biases manifest in CE decision-making processes? To what extent do these biases hinder or promote sustainable practices? What strategies can mitigate the negative impact of biases, and how can stakeholders leverage positive biases to enhance sustainability outcomes? This model aims to shed light on these complex dynamics, offering insights into the behavioural aspects of decision-making in the CE.

Table 15. DSR summary for section vs thesis - Model Development 7

DSR applied to this model	DSR applied to the thesis
Problem identification and motivation. Define objectives for the solution. Design and development of the artefact. Demonstration. Evaluation. Communication.	Demonstration. (In Section 8)

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This methodology integrates both qualitative and quantitative approaches, incorporating conceptual and empirical methods to investigate decision-making dynamics, as seen in Table 15. Central to the approach is developing a new CLD grounded in research on cognitive biases, behavioural economics, and CE principles listed in Sections 1 and 2. This model captures the relationships between cognitive biases, stakeholder behaviour, and CE decision-making processes. The themes identified from the literature are listed in Table 16 below.

Table 16. Conceptual CLD variable discussion - Model Development 6

Variable	Discussion	Variable	Discussion
Media Influence (MI)	Media influence refers to the impact various media channels, including news outlets, social media, and advertisements, have on an individual's perception of sustainability and environmental issues. Positive media coverage can raise awareness and encourage individuals to adopt sustainable practices, while negative or misleading coverage can lead to scepticism and resistance (Gordon, 2018:17-46).	Agreement with Sustainable Practices (ASP)	Agreement with sustainable practices indicates the degree to which individuals believe in and support actions and behaviours that promote sustainability. This variable reflects how much a person aligns with principles such as recycling, conservation, and responsible consumption (Sajjad et al., 2024:2849-2867).
Response to Information (RI)	Response to information measures how individuals react to new information or media that challenges their views on sustainability and the environment. Positive responses might include a willingness to adapt and change behaviours, while negative responses may lead to scepticism or resistance (Caled and Silva, 2022:123-159).	Agreement with Fossil Fuel Reduction (FFR)	Agreement with fossil fuel reduction represents an individual's stance on the need to decrease the use of fossil fuels in favour of cleaner, sustainable energy sources. A higher level of agreement suggests a preference for renewable energy and efforts to reduce carbon emissions (Achakulwisut et al., 2023:5425).
Behaviour Change (BC)	Behaviour change refers to adopting new practices or habits that align with sustainability goals. This can include consumption patterns, waste management, and energy usage changes. Positive behaviour change is essential for achieving sustainability targets at an individual and societal level (Berkman, 2018:28-44).	Agreement with Public Awareness (PA)	Agreement with public awareness measures how much individuals believe in raising awareness about environmental issues and sustainability. The high agreement suggests support for education and outreach efforts to inform the public and drive change (Calculli et al., 2021:129244).

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Willingness to Change Habits (WH)	Willingness to change habits assesses an individual's openness to modifying their lifestyle and consumption patterns to support sustainability and environmental protection. A strong desire indicates a readiness to embrace new practices aligned with sustainable living (Lubowiecki-Vikuk et al., 2021:91-101).	Individual Action (IA)	Individual action evaluates the extent to which a person takes personal initiative to support sustainability efforts. This includes reducing waste, conserving resources, and advocating for environmental causes (Sheng et al., 2023:709-723).
Cognitive Bias Impact (CBI)	Cognitive bias impact examines how an individual's biases, such as confirmation bias or status quo bias, affect their perception of and engagement with sustainability practices. The high impact of cognitive biases can hinder the adoption of sustainable behaviours (Mouad and Zakia, 2023:457-457).	Technology and Innovation Impact (TI)	Technology and innovation impact assesses the belief in the potential of new technologies and innovative solutions to address environmental challenges. A high perceived impact suggests confidence in the role of technology in promoting sustainability (Al-Emran and Griffy-Brown, 2023:102240).
Business Sustainability Priority (BSP)	Business sustainability priority evaluates how much individuals believe businesses should prioritise sustainability in their decision-making processes. This includes ethical sourcing, waste reduction, and sustainable product design considerations (Benkert, 2021:441-456).	Belief in Human-Caused Climate Change (CC)	Belief in human-caused climate change measures the extent to which individuals attribute climate change to human activities such as greenhouse gas emissions. A strong belief in this connection often motivates individuals to support policies and practices to mitigate climate change (Milfont et al., 2017:1-5).
Cognitive Bias Influence (CBI2)	Cognitive bias influences how an individual's biases shape their approach to change and innovation within the CE. This includes resistance to adopting new practices due to entrenched habits or scepticism towards new information. While both variables deal with the influence of cognitive biases, CBI1 focuses on the impact of biases on decision-making and sustainable practices. At the same time, CBI2 examines how biases contribute to resistance to change and the adoption of	Resistance to Change (RC)	Resistance to change evaluates the degree to which individuals oppose or hesitate to change their habits or adopt new practices. High resistance may stem from cognitive biases, lack of information, or entrenched norms, posing challenges to sustainability initiatives (Constantino et al., 2022:50-97).

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	CE practices (Palmucci and Ferraris, 2023:1130059).		

Some of the survey questions are also analysed to create the new CLD. Table 17 shows the questions evaluated in this study.

The analysis involves coding the survey data from Appendix C – Raw data from surveys to identify patterns, themes, and relationships between cognitive biases and decision-making behaviours. See Appendix I – Model Development 7 for the Atlas.ti methodology.

Table 17. Survey questions and discussions - Model Development 7

Question number in the survey	Question	Discussion
Question 6:	"Which of the following factors will convince you to buy/use sustainable products?"	This question explores the decision-making factors related to sustainability, providing insights into what influences individuals in choosing sustainable options.
Question 7:	"Are you willing to change your habits to be more sustainable?"	This question directly addresses the willingness of individuals to change their behaviours for the sake of sustainability, shedding light on their openness to adopting CE practices.
Question 10:	"How do you respond to information or media that challenges your views on sustainability and the environment?"	Understanding individuals' responses to challenging information about sustainability can help reveal potential cognitive biases in their perceptions and decision-making processes.
Question 12:	"How much do you believe that cognitive biases can impact the success or failure of CE initiatives?"	This question directly addresses the perceived influence of cognitive biases on CE initiatives, providing valuable insights into participants' awareness of cognitive biases in this context.
Question 14 (multiple statements):	"To what extent do you believe cognitive biases influence decision-making in adopting CE principles and practices?" "To what extent do you think that cognitive biases play a role in the resistance to change and adoption of CE practices?"	Several statements within Question 14 are relevant to understanding individuals' beliefs and attitudes toward sustainability, environmental practices' importance, and cognitive biases' role in decision-making.

The coding process involves both deductive and inductive methods. Predefined codes based on the research framework are applied deductively, while new themes emerge inductively from the data. This dual approach ensures a more comprehensive understanding of the cognitive biases at play and their impact on CE decision-making.

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This CLD development adopts an iterative process, continuously refining the CLD based on both literature insights and empirical data. The dynamic hypothesis guiding the study suggests that cognitive biases significantly influence decision-making processes in the CE, either promoting or hindering sustainable practices. By identifying feedback loops within the system, the study aims to reveal leverage points for effective intervention, as seen in Figure 43.

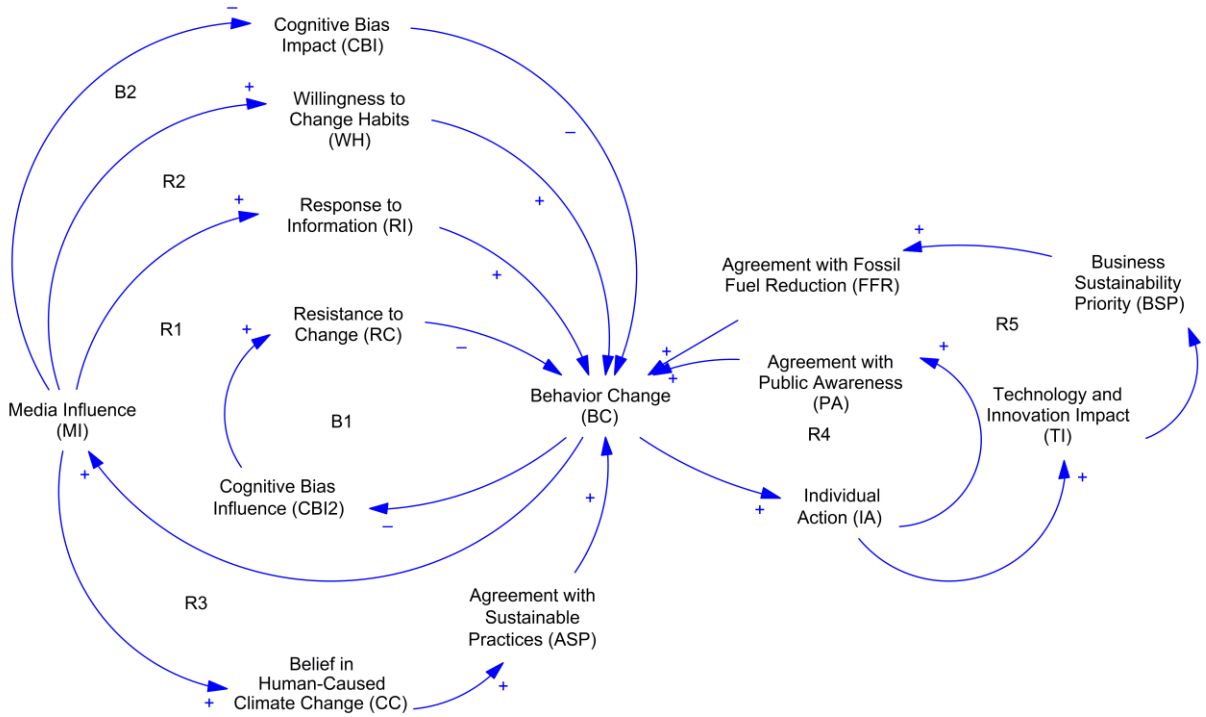

Figure 43. Conceptual CLD, validated with survey data - Model Development 7

The research employs grounded theory methodology to validate the relationships within the CLD. Grounded theory allows for the iterative development and refinement of theoretical constructs based on empirical evidence, ensuring that the model reflects real-world dynamics, as seen in Table 18.

Table 18. Variables connection and discussions - Model Development 7

Variable connection	Connection discussion	Proven by survey or literature
MI to RI	Positive media influence may lead to a positive response to information. Negative media influence may lead to an adverse reaction to information.	Survey data: Grounded frequency of MI=48 Grounded frequency of RI=37 Co-occurrence = 26
RI to BC	Positive and open responses to information may lead to increased sustainable behaviour. Adverse reactions to information may lead to decreased sustainable behaviour.	Survey data: Grounded frequency of BC = 30 Co-occurrence = 13 Positive Co-occurrence = 32 Neutral Co-occurrence = 14 Negative Co-occurrence = 22

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BC to MI	Describes how increased sustainable behaviour can lead to more positive or supportive media coverage of sustainability issues.	Survey data: Co-occurrence = 14 Positive Co-occurence = 35 Neutral Co-occurence = 17 Negative Co-occurence = 26
MI to WH	Indicates how increased media coverage and information about sustainability can lead to a higher willingness to change habits to align with sustainable practices.	(Hase et al., 2021:102353; Kannengießer, 2021:323-338; Wonneberger et al., 2020:176-193)
WH to BC	A high willingness to change habits may lead to increased sustainable behaviour. A low desire to change habits may lead to no change or decreased sustainable behaviour.	Survey data: Question 7, 78 answered Yes, and one answered No.
MI to CBI	Suggests that increased media influence can mitigate the impact of cognitive biases on decision-making, leading to more rational and informed choices.	(Ehrlinger et al., 2016; Korteling et al., 2023:1129835; Petrie et al., 2024:121-127)
CBI to BC	A high perceived impact of cognitive biases may lead to decreased sustainable behaviour.	Survey data: Question 12, 33 answered Very likely, 30 answered Somewhat likely, 11 answered Neither likely nor unlikely, four answered Somewhat unlikely, and one responded Very unlikely.
MI to CC	Increasing media influence on climate change topics can strengthen individuals' belief in human-caused climate change.	Survey data: Grounded frequency of CC = 31 Co-occurrence = 10 Positive Co-occurrence = 35 Neutral Co-occurrence = 16 Negative Co-occurrence = 30
CC to ASP	Shows how a strong belief in human-caused climate change can lead to a more remarkable agreement with and support for sustainable practices.	(Milfont et al., 2017:1-5; Kerr and Wilson, 2018:200)
ASP to BC	Agreement with sustainable practices may positively influence behaviour change.	(Klaniecki et al., 2018; Mastria et al., 2023:15429)
BC to CBI2	Suggests that increased sustainable behaviour can decrease cognitive biases influencing decision-making and resistance to change.	Survey data: Question 14.1, 2 answered Strongly disagree, 1 answered Disagree, nine answered Neither agree nor disagree, 45 answered Agree, and 22 responded Strongly agree.
CBI2 to RC	The high perceived influence of cognitive biases may contribute to resistance to change.	Survey data: Question 14.2, 2 answered Strongly disagree, 2 answered Disagree, four answered Neither agree nor disagree, 44 answered Agree, and 27 responded Strongly agree.
RC to BC	Illustrates how increased resistance to change can lead to decreased sustainable behaviour.	(Warrick, 2023:433-441; Whitmarsh et al., 2021:76-81; Seniuk et al., 2019:911-926)

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BC to IA	More sustainable behaviour may positively influence higher individual action.	Survey data: Grounded frequency of IA = 23 Co-occurrence = 14 Positive Co-occurrence = 25 Neutral Co-occurrence = 13 Negative Co-occurrence = 15
IA to PA	Demonstrates how increased individual action can raise public awareness of sustainability issues.	(Khatibi et al., 2021:18; Hao et al., 2022:1-11)
PA to BC	Agreement with the importance of public awareness may positively influence behaviour change.	(Ivanaj, 2024:3; Maibach, 2019:336-346)
IA to TI	Shows how increased individual action can contribute to the impact of technology and innovation on sustainability.	Survey data: Grounded frequency of TI = 4 Co-occurrence = 1 Positive Co-occurrence = 11 Neutral Co-occurrence = 8 Negative Co-occurrence = 9
TI to BSP	Indicates how a higher impact of technology and innovation can lead to more excellent business prioritisation of sustainability.	(Sagar, 2023; McCausland, 2021:59-63)
BSP to FFR	Increasing business emphasis on sustainability can lead to more significant efforts to reduce fossil fuel usage.	(Udeagha and Muchapondwa, 2023:1638-1651; Wang and Zhang, 2023:104-324; Araújo and de Medeiros, 2021:1385-1388)
FFR to BC	Agreement with fossil fuel reduction may positively influence sustainable behaviour.	Survey data: Grounded frequency of FFR = 10 Co-occurrence = 3 Positive Co-occurrence = 20 Neutral Co-occurrence = 10 Negative Co-occurrence = 11

The CLD in Figure 43 has several balancing and reinforcing loops, as discussed in Table 19 below.

Table 19.Feedback loops and discussions - Model Development 7

Feedback Loops	Discussion	Feedback Loops	Discussion
Reinforcing Loop (R1)	High MI → Positive RI → Increased BC → High MI (a cycle of positive reinforcement) Low MI → Negative RI → Decreased BC → Low MI (a cycle of negative reinforcement)	Reinforcing Loop (R2)	High WH → Increased BC → Positive MI → High WH (a loop reinforcing positive responses and increased sustainable behaviour) Low WH → No/Decreased BC → Negative MI → Low WH (a loop reinforcing less willingness, negative responses, and decreased sustainable behaviour)
Reinforcing Loop (R3)	High MI → Strong Belief in Human-Caused Climate	Reinforcing Loop (R4)	Increased Behavior Change (BC) → High

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	Change (CC) → Strong Agreement with Sustainable Practices (ASP) → Increased Behavior Change (BC) → High MI (a cycle of positive reinforcement)		Individual Action (IA) → Strong Agreement with Public Awareness (PA) → Increased Behavior Change (BC) (a cycle of positive reinforcement)
Reinforcing Loop (R5)	Increased Behavior Change (BC) → High Individual Action (IA) → High Technology and Innovation Impact (TI) → Strong Business Sustainability Priority (BSP) → Strong Agreement with Fossil Fuel Reduction (FFR) → Increased Behavior Change (BC) (a cycle of positive reinforcement)	Balancing Loop (B1)	Increased Behavior Change (BC) → Decreased Cognitive Bias Influence (CBI2) → Decreased Resistance to Change (RC) → Increased Behavior Change (BC) (a cycle of balancing reinforcement)
Balancing Loop (B2)	Increased Media Influence (MI) → Decreased Cognitive Bias Impact (CBI) → Increased Behavior Change (BC) → Increased Media Influence (MI) (a cycle of balancing reinforcement)		

Subsequently, the refined CLD is integrated into the CLD from Figure 38, which enables the visualisation of CE systems, enriching the model's comprehensiveness and ensuring that it reflects the latest insights from both literature and empirical research.

The model in Figure 44 provides valuable insights into how cognitive biases influence decision-making, allowing stakeholders to identify leverage points for promoting sustainable practices. See Section 8 for more discussions.

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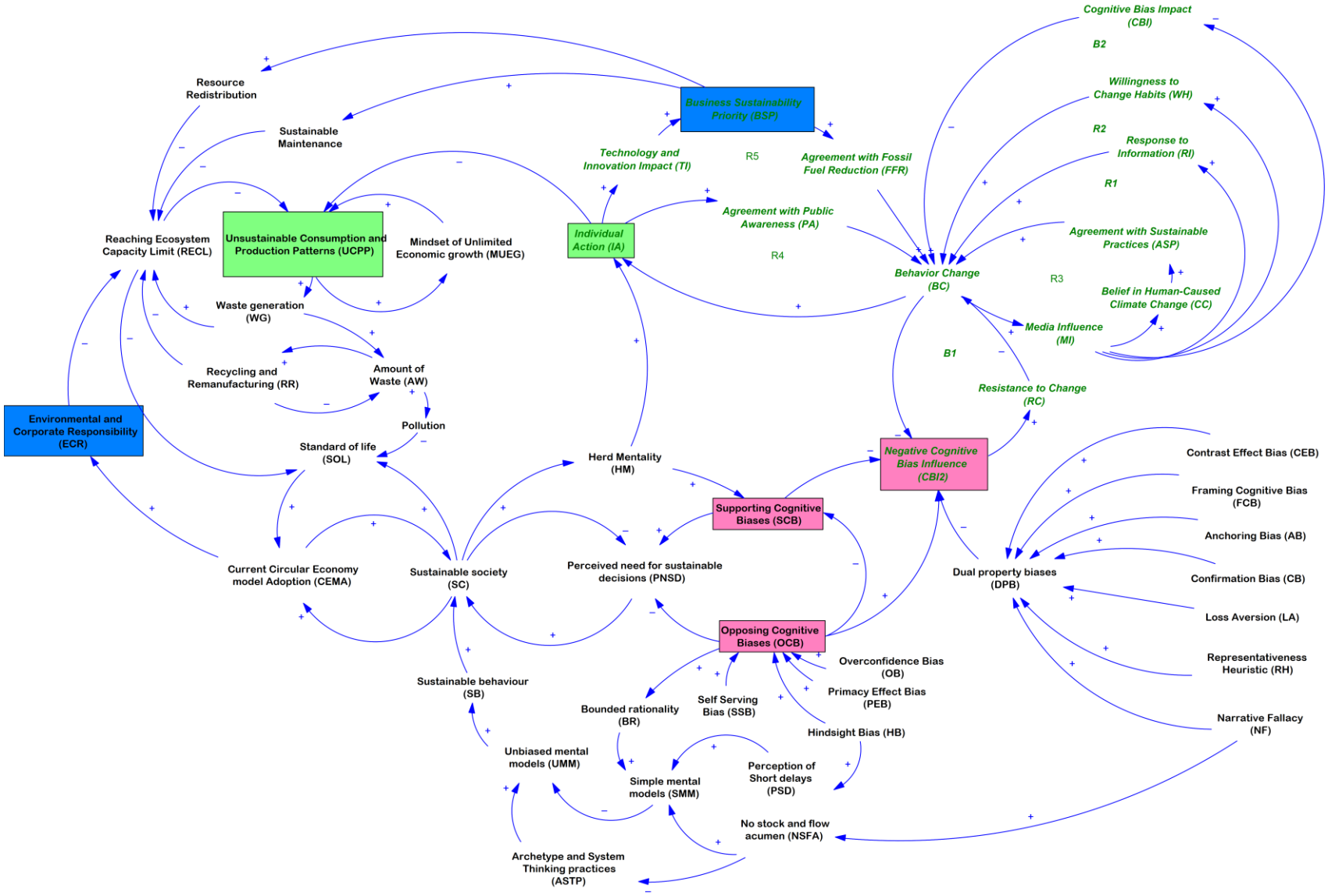

Figure 44. Merged CLD from Model Development phases

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The last step of the process is to merge the new CLD variables into the existing SFD from Figure 40.

The new SFD in Figure 45 presents an enhanced representation of the CE system, incorporating key variables such as Media Influence, Response to Information, and Behaviour Change. The updated SFD allows for a comprehensive analysis of how these variables impact the system's behaviour, offering insights into practical strategies for advancing sustainability.

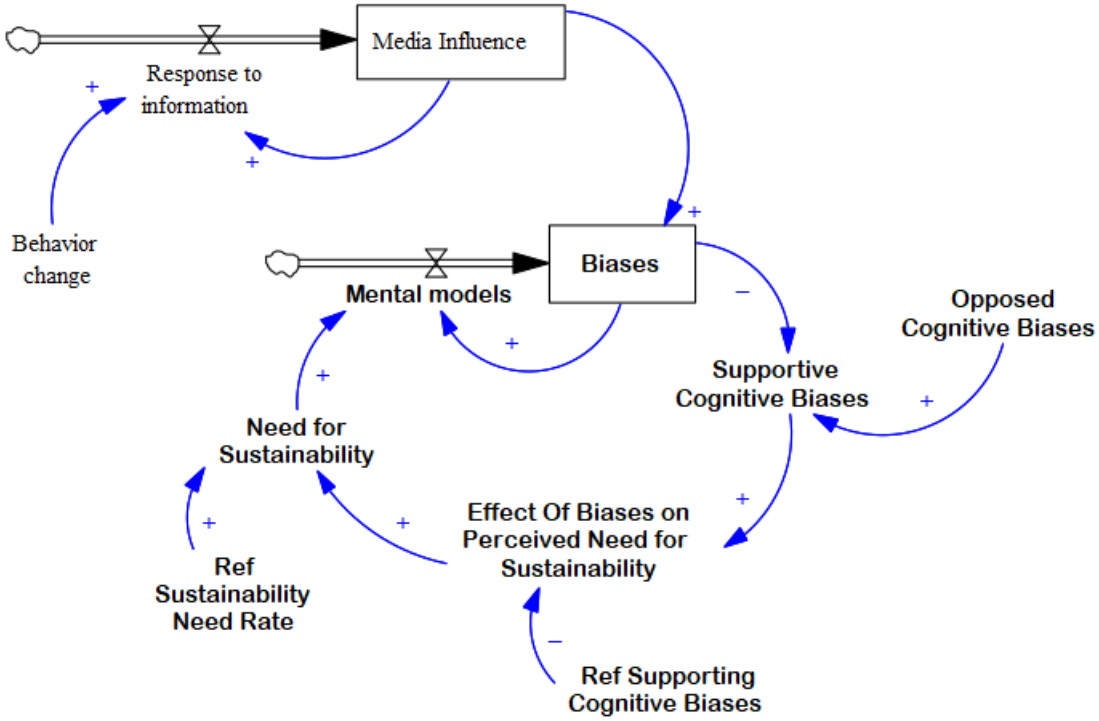

Figure 45. Merged SFD from Model Development phases

The survey answers were incorporated into the SFD by translating grounded frequencies from qualitative data into quantitative values. Using Atlas.ti, the survey responses were coded and categorised into positive, neutral, and negative frequencies, reflecting participants' attitudes and perceptions regarding sustainability and biases.

These frequencies were then used to assign quantitative values to critical variables in the model, such as media influence, response to information, and behaviour change. Positive frequencies indicated a favourable stance toward sustainability, neutral frequencies represented ambivalence, and negative frequencies suggested resistance or scepticism.

The SFD could accurately reflect stakeholder attitudes and biases by converting these qualitative insights into numerical data, providing a more precise and nuanced

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representation of the system's dynamics. This approach enabled the model to account for participant response variations, enhancing the simulations' reliability and the subsequent analysis.

See Table 20 and Table 21 for a discussion on the stocks and variables. The simulations are shown in Section 8.1.

Table 20. Stock and flow diagram - Stock discussions

Stock	Discussion	Initial conditions and sensitivity analysis conditions (SAC)
Stock 1: Biases	This stock represents the accumulation of cognitive biases within the system. Cognitive biases can impact individuals' perceptions, decision-making, and behaviour related to sustainability.	Initial value from (van der Linde et al., 2023:5-18) =201 SAC: LowerOpp case = 100
Stock 2: Media Influence	This stock represents the impact of media on individuals' perceptions and attitudes towards sustainability. Positive or negative media coverage can influence how individuals perceive sustainability issues. Survey frequencies from thematic analysis: Grounded frequency = 48 Positive = 20 Neutral = 10 Negative = 18	Initial value = 20 SAC: BaseCase, LowerOpp, HigherCap = Response to information*(1-Media Influence/48) SAC: NegInfl = (Response to information)*(1-Media Influence/48)-18*(18/48)

Table 21. Stock and flow diagram - Variables discussions

Variable	Discussion	Initial conditions, rate of flow, and sensitivity analysis conditions (SAC)
Supportive Biases and Opposing Biases	These variables influence the accumulation of biases (Stock 1). Supportive biases encourage individuals to support sustainable practices, while opposing biases discourage them.	Ref Supportive=0.80 (van der Linde et al., 2023:5-18) Equation 3, as described above Opposing Cognitive biases =1015 (capacity) SAC: HigerCap = Opposing Cognitive biases =2030(capacity)
Effect of Biases on Perceived Need for Sustainability	This variable captures how biases impact individuals' perceived need for sustainability. It influences the degree to which people recognise and prioritise sustainable practices.	Equation 2, as described above

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Need for Sustainability	This variable represents the actual need for sustainable practices within the system. The effect of biases on the perceived need for sustainability influences it.	Reference Sustainability Need Rate = 0.134 (van der Linde et al., 2023:5-18) Equation 1, as described above
Mental models	The mental model variable is a critical component of the SFD flow model, as it influences how individuals perceive and engage with sustainability issues. By understanding the interplay between mental models, biases, and other variables, stakeholders can design more effective strategies to promote sustainable practices and advance the CE.	=Biases x Need for Sustainability
Response to Information	This variable represents how individuals react to new information about sustainability. Positive responses can lead to changes in behaviour, while negative responses may reinforce existing biases. Survey frequencies from thematic analysis: Grounded frequency = 37 Positive = 17 Neutral = 7 Negative = 14	SAC: BaseCase, LowerOpp, HigherCap =17*Behavior change*(1-Media Influence/37) SAC: NegInfl = 14*Behavior change*(1-Media Influence/37)
Behavior Change	This variable represents changes in individual behaviours towards more sustainable practices. It can be influenced by the response to information and the perceived need for sustainability. Survey frequencies from thematic analysis: Grounded frequency = 30 Positive = 15 Neutral = 7 Negative = 8	SAC: BaseCase, LowerOpp, HigherCap =15/30 SAC: NegInfl =8/30

In conclusion, the model developed in this study serves as a critical resource for understanding and addressing the behavioural dimensions of decision-making within the CE.

By uncovering the cognitive biases that influence stakeholders' choices, the study offers practical strategies for promoting sustainable practices and advancing the transition towards a more circular and sustainable economy.

3.4. Interlinkages between Models

All the models and frameworks from the top sections are linked, as seen in Figure 46.

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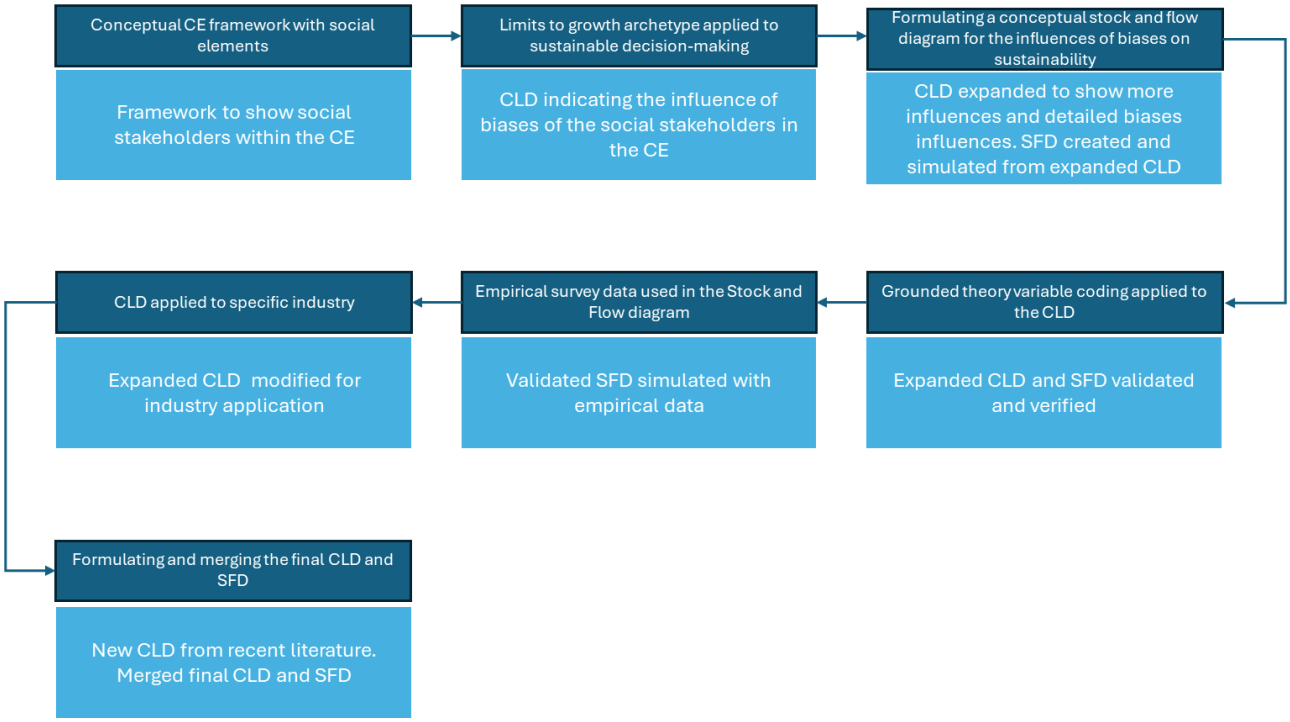

Figure 46. Interlinkages between Models in Model Development Phases

3.5. Conclusion

This chapter has established the groundwork for integrating these models into a cohesive thesis using DSR. Integrating the models early in a thesis allows for a more holistic understanding of the SD around sustainability and biases and enables the simulation of different scenarios to predict potential outcomes under varying conditions.

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4. Conceptual Model

Building on the literature review, Section 4 focuses on developing a theoretical model for sustainable decision-making. This involves defining system boundaries and applying various systems approaches.

Imagine constructing a bridge designed to withstand any storm yet failing because the team overlooked how the community's fear of crossing it during high winds would keep people away. In this chapter, the researcher develops a conceptual model that similarly bridges SE with insights into cognitive biases. Just as a bridge must consider both engineering principles and human attitude to be effective, the model synthesises technical and mental elements to create a framework that reflects the realities of decision-making in the CE. The research argues that without addressing cognitive biases, even the most robust technical models fail to guide stakeholders toward genuinely sustainable outcomes. This section fits into the DSR framework of the thesis, as shown in Figure 47.

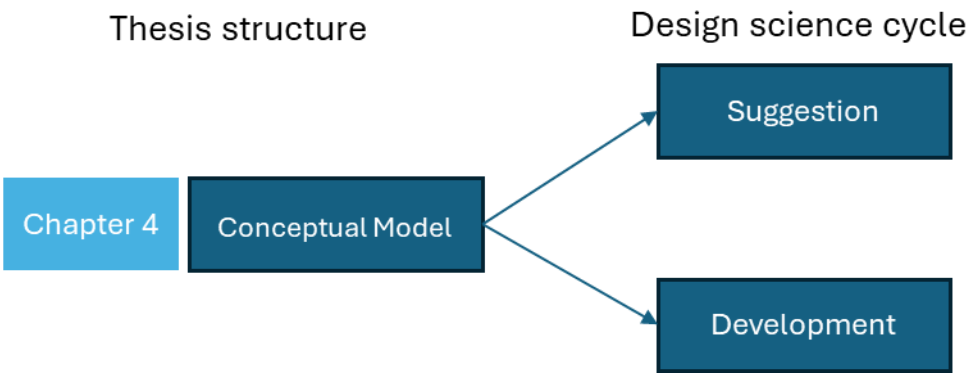

Figure 47. Design Science Research Framework - Chapter 4

4.1. Introduction

This section aims to provide details about the models developed in Chapter 3 to show how the models can serve as powerful tools, facilitating the comprehension and identification of biases in a structured and methodical manner. By integrating thematic content analysis into the model, the research aims to discern recurring patterns, themes, and language that reveal the presence of biases in various contexts. Moreover, the study will explore how external factors such as culture, socio-economic influences, and institutional policies intertwine with individual cognitive processes to shape decision-making outcomes.

The DSR methodology development phase is addressed in the conceptual systems model. This phase embodies the transformative journey from ideation to tangible artefact creation, where theoretical concepts take shape into practical solutions. Within

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this framework, the development phase serves as the crucible, where ideas are refined, tested, and honed into actionable strategies.

Incorporating an understanding of bias into the conceptual model chapter is critical because biases, both cognitive and systemic, significantly influence decision-making processes and outcomes. Here is why addressing and mitigating bias is essential in this context:

- Enhanced decision-making: Cognitive biases like confirmation bias or anchoring can impair judgment and decision-making. By embedding bias mitigation strategies within the conceptual model, the research provides more robust frameworks for analysing decision-making processes. This leads to more objective, balanced decisions, especially in corporate governance, where biases can influence leadership choices, strategic planning, and overall fairness in organisational practices.
- Broader applicability: A conceptual model that includes mechanisms to understand and mitigate bias can be applied across a wide range of domains, from social justice initiatives to business leadership. This versatility increases the model's relevance, making it useful for addressing complex societal challenges like equity, inclusion, and ethical governance, where fairness and impartiality are critical.

Pursuing impartiality and objectivity in decision-making remains a formidable challenge in human interactions and organisational dynamics. Whether overt or subtle, bias permeates our thoughts, actions, and judgments, often leading to unintended consequences and inequitable outcomes. As societies strive for greater inclusivity and fairness, understanding and mitigating bias have become paramount in numerous domains, ranging from social justice to corporate governance.

In the following section, the models developed in Sections 3.3.2, 3.3.3 and 3.3.4 are discussed in detail as part of the overall DSR approach to the thesis.

4.2. System Boundary Definition

In systems modelling, defining the boundaries of a model is a critical step that profoundly impacts the accuracy and effectiveness of the analysis. The boundary of a system delineates the scope of inquiry, specifying what is included within the model and what lies outside of it. Determining these boundaries is not a straightforward task, as they are subject to multiple interpretations and can significantly influence the outcomes of the analysis (Checkland and Poulter, 2006:200). The process of boundary definition involves grappling with complex trade-offs, considering what elements to include to ensure relevance and completeness while avoiding undue complexity that could hinder comprehension (Richardson, 2011:219-243).

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Adequate boundary definitions demand a profound understanding of the interconnectedness and interdependencies between system components (Sterman, 2000:982; Ulrich and Reynolds, 2020:255-306; Desing et al., 2020:2-5). The literature emphasises the dynamic nature of systems, underscoring the need to account for feedback loops, time delays, and causal relationships that extend beyond traditional linear perspectives (Meadows et al., 2006:397-399). By incorporating these insights, researchers can construct systems models that capture the complexities of real-world scenarios and provide a more accurate representation of the underlying dynamics (Forrester et al., 2018:61-75).

Despite the recognised importance of boundary definitions, challenges abound in determining the appropriate scope for a systems model. One key challenge lies in the inherent subjectivity of the process, where researchers' perspectives and biases can unintentionally influence what is included or excluded from the analysis (Vennix, 1999:379-401). Furthermore, stakeholder perspectives may differ, leading to varying interpretations of what constitutes the relevant system components (Maani and Maharaj, 2004:21-48). This divergence in viewpoints can create tensions during the boundary definition phase, necessitating transparent communication and a collaborative approach to ensure inclusivity and acceptance of the final model.

Moreover, the dynamic and evolving nature of systems presents another challenge. As external factors influence systems and adapt to changing environments, static boundary definitions may quickly become obsolete (Michaelis et al., 2021:1797-1820). Maintaining the relevance of systems models over time requires continuous monitoring and adaptation of boundaries to capture emerging complexities and evolving relationships (Ruth and Hannon, 2012:35-52).

Researchers have proposed various approaches and methodologies to address the challenges inherent in boundary definition. One notable framework is the Soft Systems Methodology (SSM) by Checkland (1999:45-56), which emphasises a holistic and qualitative approach to defining boundaries. SSM encourages stakeholders to engage in a structured dialogue to identify relevant components, perspectives, and issues, fostering a shared understanding of the system's boundaries, as discussed in Section 2.4.2.

Another valuable contribution comes from the work of Nabavi et al. (2017:312-323), who advocate for a multi-level boundary analysis. Their approach acknowledges the existence of multiple nested systems, each with its boundaries, and highlights the importance of exploring interactions across different levels to understand the overall system comprehensively.

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These diverse approaches to boundary definition, informed by a rich body of literature, offer valuable insights into the complexities of systems modelling and serve as helpful tools for researchers seeking to construct accurate and impactful models (Javanmardi et al., 2023:70; Westra and Zscheischler, 2023:645-655; Bozeman III et al., 2023:382-394).

In the context of this study on bias identification and decision-making influences, the research has adopted the SSM as a practical and valuable approach to defining the system's boundaries under investigation. By employing SSM, the study aims to comprehensively analyse bias identification and decision-making influences while incorporating multiple perspectives from diverse stakeholders.

In the study on bias identification and decision-making influences, the research utilised the SSM as a practical approach to defining the system's boundaries under investigation. By employing SSM, the study aims to ensure a comprehensive analysis of bias identification and decision-making influences while considering the intricate complexities of the system. Figure 48 below illustrates the focal issue examined in this study, indicating that the social components within the CE model exhibit a predisposition towards sustainable choices. The recommended remedy involves adopting a decision-making framework that counteracts unsustainable biased decisions by integrating tools rooted in ST principles.

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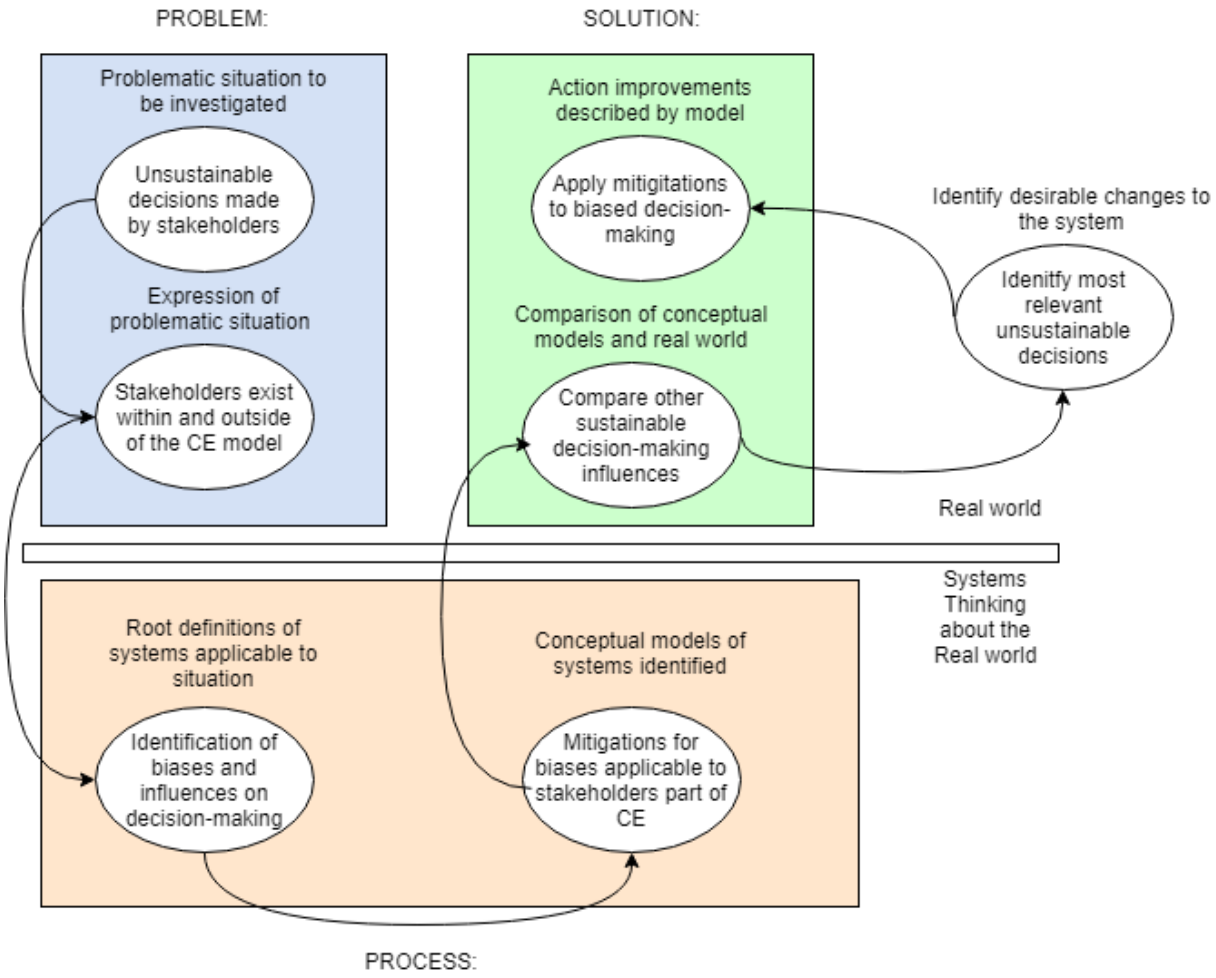

Figure 48. SSM applied to the problem of biased decision-making in the CE (van der Linde et al., 2022:2-11)

See Section 3.3.2 for more details on the process followed for the model development.

The implementation of SSM in Figure 48 involved employing various techniques, such as rich pictures, root definitions, and conceptual models. It uniquely integrates SSM with identifying and mitigating cognitive biases, offering a fresh perspective on how stakeholder dynamics can be systematically analysed within the CE framework. Rich pictures were utilised to visually express the system's perceptions, concerns, and understanding, including any potential bias-related issues that could impact decision-making processes. Root definitions were employed to provide a clear articulation of the purpose and objectives of the system, enabling the researcher to identify the underlying values and goals that may influence decisions and introduce biases.

Through careful consideration and analysis of the system's decision-making processes, internal and external influences contributing to bias were examined. The researcher gained valuable insights into the factors that shape decision-making outcomes by delving into the system's dynamics and acknowledging potential biases.

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Developing a conceptual model visually represented the system and its boundaries, incorporating the identified biases and decision-making influences. This model considered various elements, such as feedback loops, causal relationships, and dynamic interactions, offering a comprehensive representation of the complexity inherent in real-world systems.

Furthermore, the iterative nature of SSM allowed the researcher to continuously refine and adapt the boundary definition as new insights emerged during the research process. This flexibility enabled the researcher to adjust the conceptual model to accommodate changes in understanding and better reflect the evolving dynamics of the system.

In conclusion, applying the SSM in the study on bias identification and decision-making influences has provided a structured and insightful approach to system boundary definition. The researcher comprehensively understood the potential biases impacting the system within the specified boundaries by utilising SSM techniques and exploring various decision-making influencers. This understanding lays the groundwork for informed and impactful interventions to mitigate biases and promote more equitable and inclusive decision-making processes.

4.3. Thematic Content Analysis Map of Bias Identification and Decision-Making Influences

Thematic content analysis mapping is a powerful and versatile methodological approach that unlocks meaningful insights and patterns hidden within large volumes of textual data. In the contemporary era of information abundance, where data is constantly generated through various sources, extracting valuable knowledge from textual content has become indispensable in academic research and practical applications (Naeem et al., 2023:1-18; Proudfoot, 2023:308-326).

Thematic content analysis mapping transcends traditional approaches to qualitative data analysis, offering a systematic framework to categorise, interpret, and visualise themes and patterns within the data (Braun and Clarke, 2012:57-69; Naeem et al., 2024:1-10). As researchers, practitioners, and decision-makers grapple with complex and multifaceted issues, such as bias identification, decision-making influences, and other socio-cultural phenomena, thematic content analysis mapping emerges as a valuable tool for sense-making and knowledge discovery (Kiger and Varpio, 2020:846-854).

In this transformative journey, the research delves into the conceptual underpinnings of thematic content analysis mapping, exploring its theoretical foundations and practical methodologies. Applying this approach to the research on bias identification

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and decision-making influences aims to unveil the nuanced complexities and underlying connections that shape human cognition and behaviour.

Throughout this study, the interdisciplinary nature of thematic content analysis mapping is embraced by drawing inspiration from linguistics, sociology, psychology, and information sciences, as discussed in Chapter 3. By adopting this diverse range of perspectives, the research aims to enrich the understanding of the relationships between themes, biases, and decision-making influences, enabling a more holistic and comprehensive exploration of the research domain (Nowell et al., 2017:1-13).

This thematic content analysis map in Figure 49 provides a structured framework for understanding and addressing biases in decision-making, illustrating the complex interplay between various influences and strategies. See Section 2.2.3 for a detailed discussion on cognitive biases with examples.

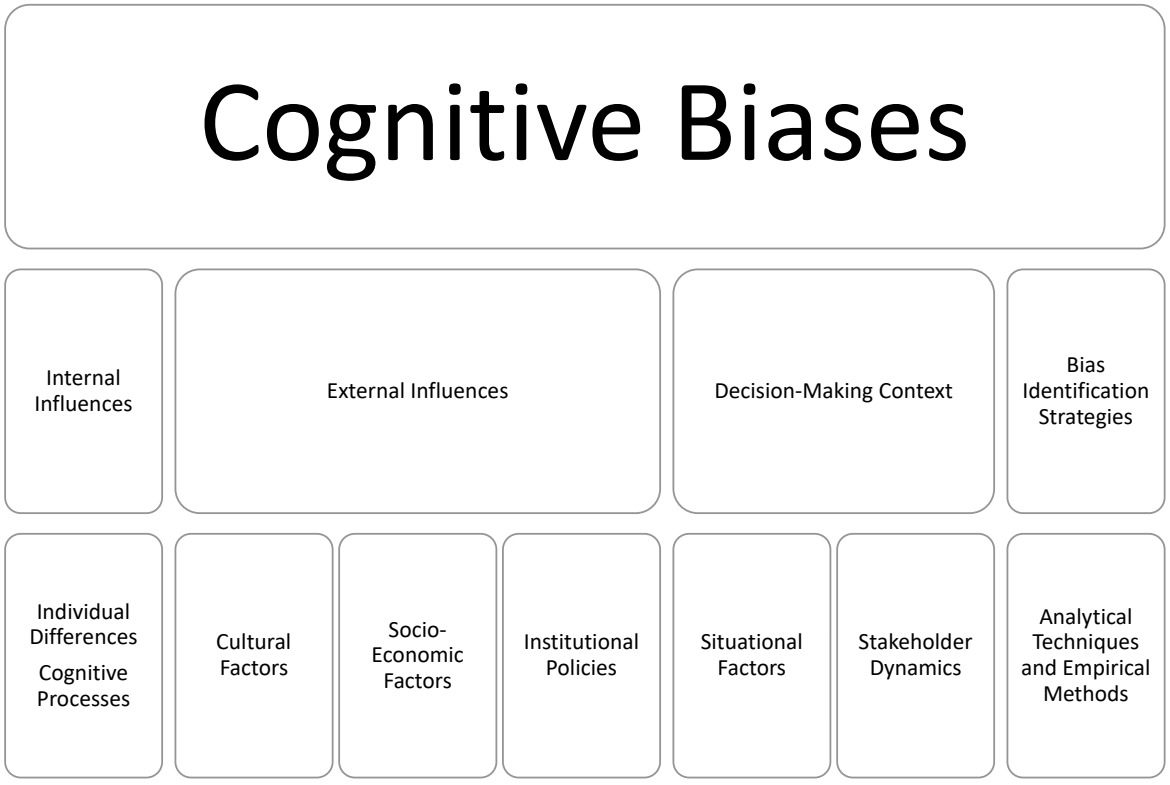

Figure 49. Thematic analysis of the study's aim

In Figure 49, cognitive biases are central to the model and directly influence decision-making, as discussed in Section 2.4. External influences such as cultural, socio-economic, and institutional factors interact with internal influences such as individual differences and cognitive processes to shape biases. The Decision-Making Context provides the situational backdrop where biases manifest, influenced by factors like time pressure and stakeholder dynamics. Bias Identification Strategies employ both analytical and empirical methods to detect biases in decision-making processes.

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Ultimately, this journey into thematic content analysis mapping opens new avenues for knowledge discovery and contributes to the ever-growing body of research to create a more informed and equitable world. As the research navigates the landscape of thematic content analysis mapping, explore this methodological approach's transformative potential, uncovering the untold stories and gaining deeper insights into the fascinating intricacies of human cognition and decision-making.

4.4. Causal Loop Diagram of Current CE Stakeholders and their Decision-Making Power

The third research question addressing the extent to which biases influence the need for sustainability in the CE is comprehensively explored by van der Linde et al. (2023:1-11) as part of and basis of this research in a paper titled "Behavioural System Dynamics: Conceptual Integration of Critical Bias Variables into Circular Economy Stakeholder Phases." This study focuses on the critical role cognitive biases play in shaping stakeholders' sustainability efforts within the CE framework relating to the RO in Section 1.5. By integrating behavioural insights into SD, the study formulates a conceptual stock and flow diagram that maps out how various biases impact sustainability initiatives over time.

The study employs the "limits to growth" archetype within its stock and flow diagram to illustrate the dynamics of bias influences on sustainability. See section 2.4.3 for literature on archetypes and Section 3.3.2 for model development with the LtG archetype. This model highlights how entrenched cognitive biases, such as short-term thinking, confirmation bias, and overconfidence, can hamper initial progress in sustainability. These biases create feedback loops that can stifle further advancements in sustainability by promoting behaviours that favour immediate gains over long-term benefits. By visualising these dynamics, the study provides a clear depiction of how biases can limit the growth and effectiveness of sustainability efforts within the CE. This approach underscores the significant impact of cognitive biases and offers a framework for identifying leverage points where interventions can most effectively mitigate these biases and foster a more sustainable CE. Through this detailed analysis, the study addresses the research question by demonstrating the profound influence of biases on the sustainability needs and actions of CE stakeholders. See section 3.3.2 for the model development and analysis discussion.

This research addresses the intersection of sustainable technology management, CE adoption, and the integration of AI. The study emphasises the growing importance of combining these elements to foster innovation and progress in technology-driven ecosystems. It highlights how AI's advanced capabilities—such as predictive modelling and data analytics—can enhance sustainable practices within technology management. The thesis also underscores the necessity of understanding the dynamic

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relationships between these components, especially in the context of global sustainability challenges. By employing a ST approach, the research aims to reveal the feedback loops and causal connections that influence decision-making in sustainable technology management, ultimately contributing to more informed and agile strategies in the adoption of CE models.

The conclusion of the research underscores the transformative potential of integrating AI within sustainable technology management initiatives, particularly in supporting CE models. The study's findings, represented through a dynamic CLD, illuminate the complex feedback loops and stakeholder dynamics that drive sustainability. The research concludes that AI integration is pivotal in optimising resource management and enhancing decision-making processes, thus significantly advancing sustainability goals. The study also highlights the broader implications of these findings for policymakers, industry leaders, and organisations, providing actionable insights to navigate the complexities of the digital era while fostering sustainability. The research contributes to the field by bridging theoretical frameworks with practical applications, offering a roadmap for future efforts in sustainable technology management.

Building on previous research in SD, CLD, Stock and Flow Diagrams (SFD), and sustainability processes and insights (Siva Muthuprakash and Damani, 2017:248-258; Penzenstadler et al., 2018:22-33), this study investigates various variables, environments, and the interactions between biases and sustainable decisions. The methodology employed in this conceptual model is a mixed-method simulation SD approach. This approach offers the advantage of a quantitatively supported simulation model to analyse and interpret specific indicators and leverage points. The mixed-method SD methodology is also utilised to identify critical variables and their interrelationships, as outlined in the different stages discussed subsequently. The CLD in Figure 50 offers a system map to illustrate the interrelationships between socioeconomic and environmental variables. The CLD was created using Vensim software, and it demonstrates that achieving a sustainable society is not an absolute goal but rather a balancing mechanism to regulate reinforcing loops. Key loops in the diagram, representing real-world dynamics, include those driven by human decision-making. The various biases influencing these decisions are linked to the mental models of decision-makers and society. The diagram features two primary loops, described as follows:

- On the left, an increased adoption rate of CE models and approaches leads to more remarkable sustainable societal development. This enhancement in sustainability subsequently boosts corporate social responsibility and the overall standard of living (Trainer and Alexander, 2019:247-60; ElAlfy et al., 2020:5544). The reinforcing loop is completed as improved societal sustainability fosters even higher adoption rates of CE models.
- The balancing loop illustrates that as society becomes more sustainable, there is a

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reduced perception of the need for additional sustainable decisions beyond current practices. This loop is completed as growth in sustainable decision-making leads to further sustainable development. These processes are influenced by various biases (supportive or opposing) and the mental models of decision-makers.

This situation exemplifies a complex problem, characterised by:

- A large number of interacting elements
- Continuous mutual influences among elements
- Dynamic relationships between elements
- Solutions that are not transparent or visible without SD
- Potential unintended consequences arising from specific actions

The following CLD innovatively maps the complex causal relationships between specific cognitive biases and the various phases of the CE, providing a detailed visualisation of how biases can either hinder or enhance sustainable practices.

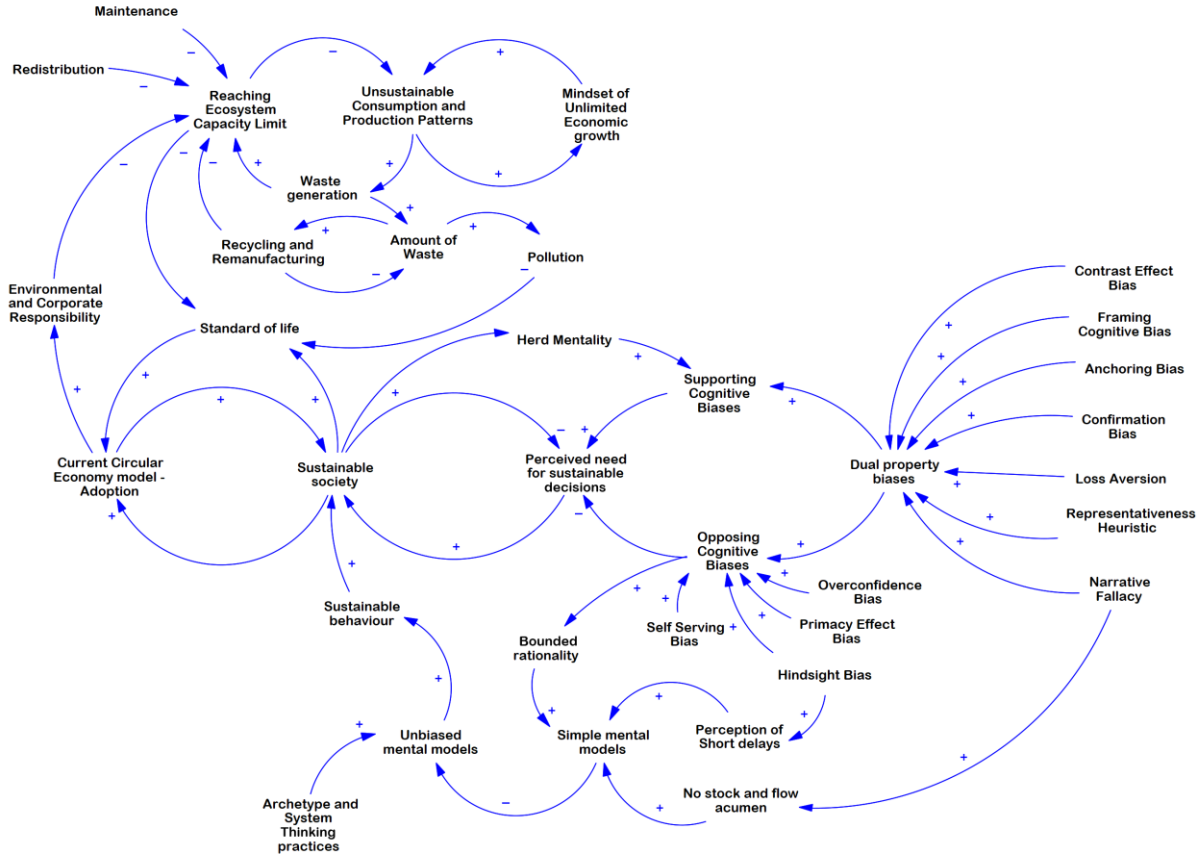

Figure 50. Causal interpretation is presented through a CLD to conceptualise critical biases in the CE phases. (van der Linde et al., 2023:1-11)

Section 4.6 identifies which CLD variables will be simulated in an SFD. Additional variables referenced in the literature will also be included. As the model undergoes iterations and is simulated with more qualitative data, these variables will be revised and expanded accordingly, as seen in 6.4.

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4.5. Validating the CE Framework with Different Bias Influences

This section only addresses the validation of the models mentioned in Chapter 4. The thesis model validation is captured in full in Chapter 7. Validation of a model is a critical step in the model development process that involves evaluating the accuracy and reliability of the model in representing real-world phenomena. Model validation ensures that the model behaves as expected and produces meaningful, accurate predictions or outputs in relation to the system it is designed to simulate or analyse (Rykiel, 1996:229-244). Model validation is essential because it confirms that the model is useful for decision-making or scientific understanding. Without proper validation, the model's outputs could lead to incorrect conclusions, poor decision-making, or misallocation of resources (Sargent, 2011:166-183).

By examining existing literature and analysing variable relationships within a behavioural CE Causal Loop Diagram (CE-CLD), this study seeks to validate the causal relationships between the variables and assess their strength. The study's findings offer valuable insights into the complex social dynamics of the CE, which can inform the development and implementation of effective strategies and policies to promote sustainability and reduce waste (Bhamra et al., 2011:427-445). Additionally, the insights gleaned from this research contribute to the broader understanding of BSD and its applicability in dissecting complex social systems like the CE (Stahel, 2016:435-438).

Grounded theory, a qualitative research approach, is crucial in validating models by offering a methodology to explore and comprehend the complex dynamics and relationships within systems such as the CE (Walsh and Rowe, 2023:653-674). Existing research showcases the application of grounded theory in validating behavioural system dynamic models, particularly in developing and validating sustainable tourism destination models. Utilising grounded theory, researchers analyse and synthesise literature, identify causal relationships, and validate these relationships within the model. The findings underscore how grounded theory enhances the validity and reliability of behavioural system dynamic models, ensuring they accurately reflect empirical evidence (Cavana et al., 2001:472).

In this section, the research method systematically analyses existing literature to ascertain and validate causal relationships within a behavioural system dynamic model of the CE. The process begins with an extensive review of pertinent studies, reports, and scholarly articles concerning the CE and BSD, aiming to pinpoint key variables, theoretical frameworks, and empirical evidence regarding their causal relationships. The initial CLD from Figure 50 lays the groundwork for identifying these variables.

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Subsequently, employing the grounded theory approach, the literature is systematically analysed to uncover patterns, themes, and relationships among the variables (Corbin and Strauss, 2008:456). This analysis involves coding and categorising data, identifying commonalities and differences, and gauging the direction and strength of causal effects. The CLD is refined through constant comparison and theoretical sampling, and relationships between variables are validated further based on empirical evidence in Chapter 8.

This research investigates applying a behavioural system dynamic model to understand and validate the causal relationships that influence decision-making in the CE. The study emphasises the complexity of the CE as a social system, where numerous interconnected variables must be managed to promote sustainability and reduce waste. The research introduces grounded theory as a qualitative approach to validate these dynamic models, offering a robust methodology to identify and evaluate the strength and direction of causal relationships within the CE framework. By focusing on the behavioural aspects and integrating them with SD, the study aims to provide deeper insights into the factors that drive or hinder the transition to a sustainable CE.

Additionally, the research design incorporates theoretical sampling, strategically selecting additional literature to address gaps and delve into specific aspects of causal relationships. The iterative process of data collection, analysis, and theory development persists until saturation is achieved, signifying that no new information or relationships emerge from the data (Glaser, 2002:9-21). A saturation test that involved randomly reserving ten journal papers before coding the remaining papers and then recoding the reserved papers with the rest was done. After this step, all the existing codes and categories coincided identically. No new codes or themes related to the paper’s topic appeared, implying theoretical saturation had been achieved.

Overall, the data collection and analysis involved an iterative literature review process, coding, and theoretical sampling, following grounded theory methodology. This approach ensures the systematic identification, refinement, and validation of the causal relationships between variables in the behavioural system dynamic model of the CE. In summary, the saturation test involved a systematic process of coding both a subset of reserved papers and the rest of the dataset, followed by a comparison to ensure consistency.

The research concludes that integrating grounded theory with SD models offers a powerful approach to understanding and validating the complex causal relationships within the CE. The study's findings demonstrate that when systematically analysed and incorporated into dynamic models, behavioural insights can significantly enhance the accuracy and relevance of these models for decision-making in sustainability initiatives. The validated model provides a better understanding of the CE's dynamics

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and is a valuable tool for policymakers, businesses, and sustainability practitioners. The research highlights the importance of continuing to refine these models through empirical studies, emphasising that future research should explore more complex dynamics and integrate behavioural insights to support the ongoing transition to a sustainable CE. Figure 51 explains the literature search and retrieval process, and Figure 52 describes the application of grounded theory.

A systematic literature review (SLR) is considered a critical review because it follows a structured, transparent, and replicable methodology to assess, synthesise, and evaluate existing research in a given field as shown in Table 3. Unlike traditional literature reviews, which may be narrative or selective, an SLR employs rigorous inclusion and exclusion criteria, comprehensive data extraction, and critical appraisal of sources to ensure objectivity and depth. This structured approach enhances the reliability and validity of the review process, making it a robust and comprehensive method for evaluating existing studies. Additionally, Grounded Theory plays a crucial role in systematically analysing and developing theoretical insights from the literature. By identifying patterns, themes, and relationships in the data, Grounded Theory enables researchers to build conceptual frameworks, ensuring that the literature review does not merely describe but contributes to theory development.

An SLR does not merely summarise previous research but critically analyses its methodologies, findings, limitations, and contributions. By assessing the quality, reliability, and relevance of the literature, it ensures that the review is not just descriptive but analytical. Furthermore, an SLR helps identify research gaps, unresolved questions, and areas for further study, providing a synthesis of key themes, trends, and debates that contribute to theoretical advancements in the field. Grounded Theory strengthens this process by allowing new concepts to emerge inductively from the literature, rather than forcing existing theoretical frameworks onto the data. This approach ensures a more nuanced and contextually relevant understanding of complex phenomena, particularly in fields like sustainability and the CE, where decision-making is shaped by evolving biases and systemic factors.

A key feature of an SLR is its ability to eliminate bias and maintain academic rigour. Unlike traditional reviews that may be prone to confirmation bias, an SLR uses predefined selection criteria to ensure an objective evaluation of all relevant literature. It also applies quantitative or qualitative synthesis techniques, such as meta-analysis or thematic coding, to derive meaningful insights. By integrating Grounded Theory into this process, researchers can move beyond surface-level analysis to develop new theoretical contributions, refining and expanding existing knowledge rather than merely reaffirming prior findings. This iterative approach is particularly valuable in fields with evolving concepts, as it ensures that research remains dynamic and responsive to emerging insights.

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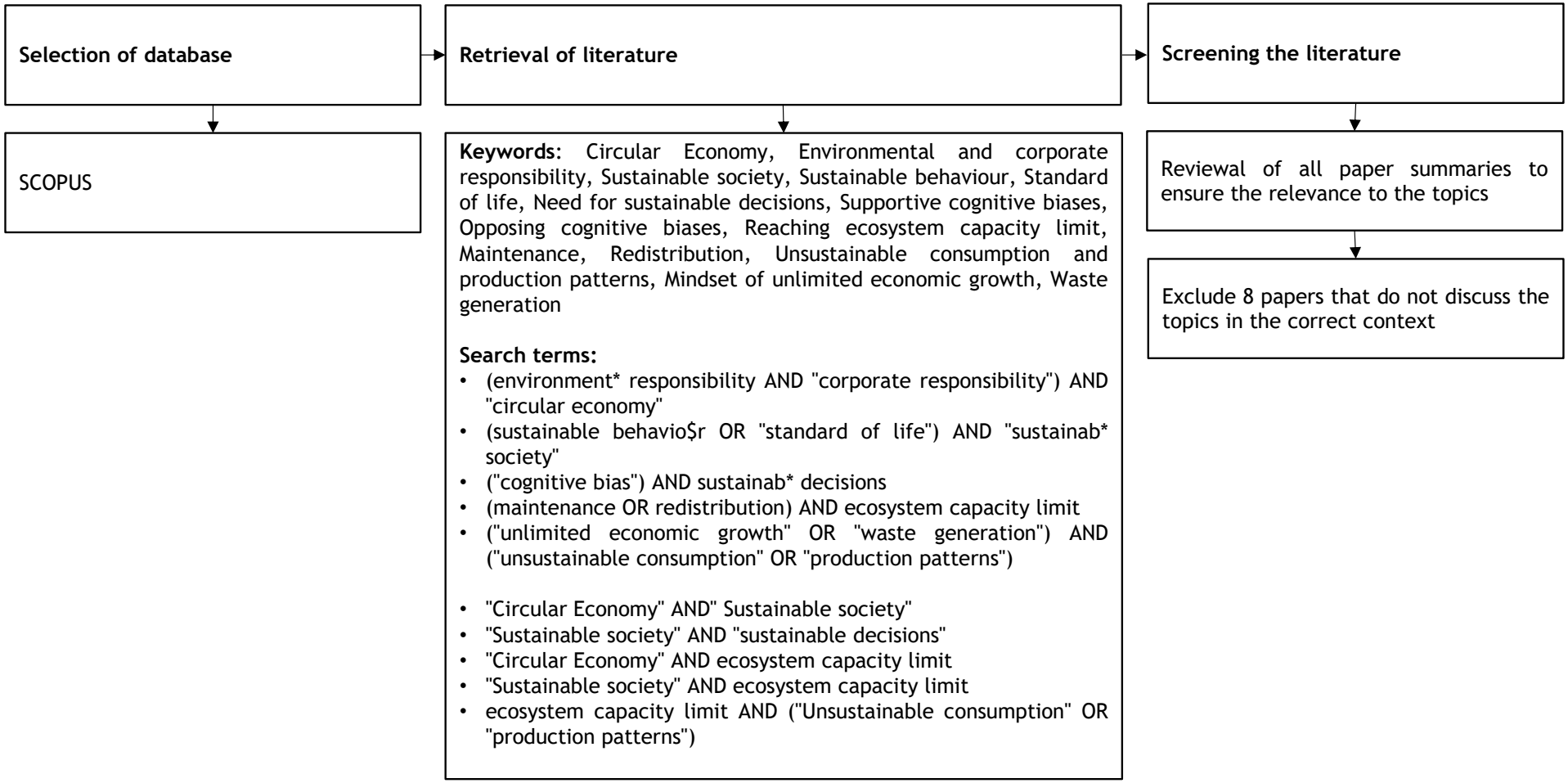

Figure 51. Literature retrieval and screening process for concept CLD validation. (van der Linde et al., 2023)

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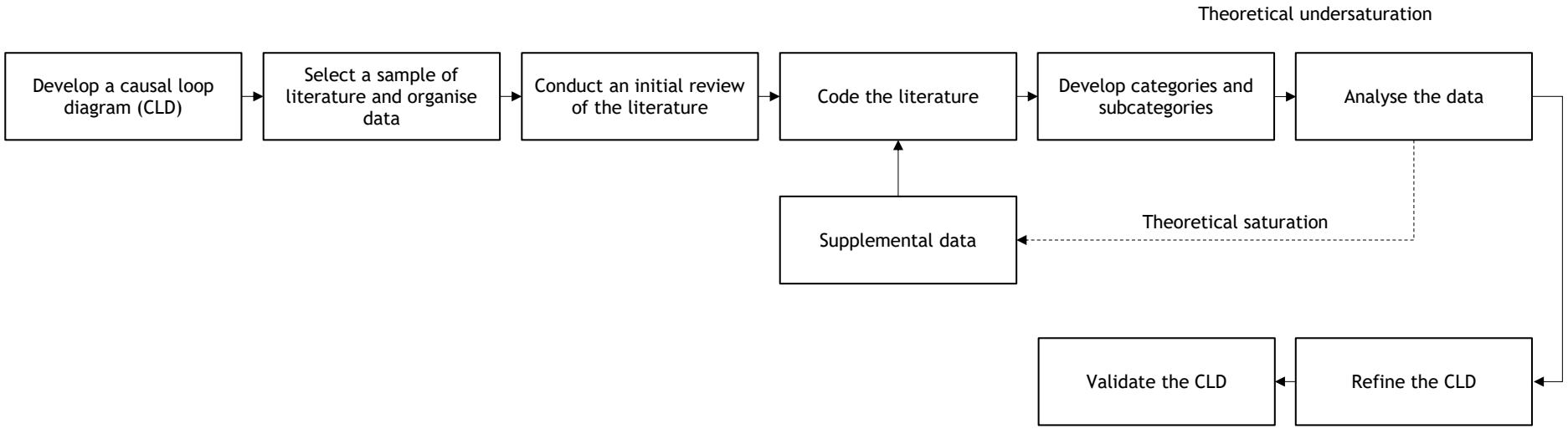

Figure 52.Grounded theory sequence as applied to CLD validation. (van der Linde et al., 2023)

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The causal effects among the CE variables can vary in direction and strength, contingent upon specific contexts and circumstances. Strong positive effects may indicate a direct and significant influence from one variable to another. For example, robust corporate social responsibility practices can drive more sustainable decision-making and greater adoption of CE principles, as seen in Figure 53. Similarly, efficient waste management strategies can directly enhance production management efficiency. However, external factors and system complexities can also influence causal effects, leading to more nuanced relationships with indirect or moderate effects. For instance, cognitive biases may hinder the adoption of circular practices, but their impact can be alleviated through awareness campaigns and educational interventions.

Furthermore, the strength and direction of causal effects may differ across sectors, industries, and regions due to various factors such as policy frameworks, technological advancements, market conditions, and cultural norms. These external influences shape the magnitude and direction of causal relationships between CE variables, emphasising the need for tailored approaches to address sustainability challenges in diverse contexts. Atlas.ti was used to compare the grounded frequencies of the CLD variables with a thematic analysis to confirm their interconnectedness. See Appendix G – Model Development 4 – Atlas.ti screenshots for more information on the analysis.

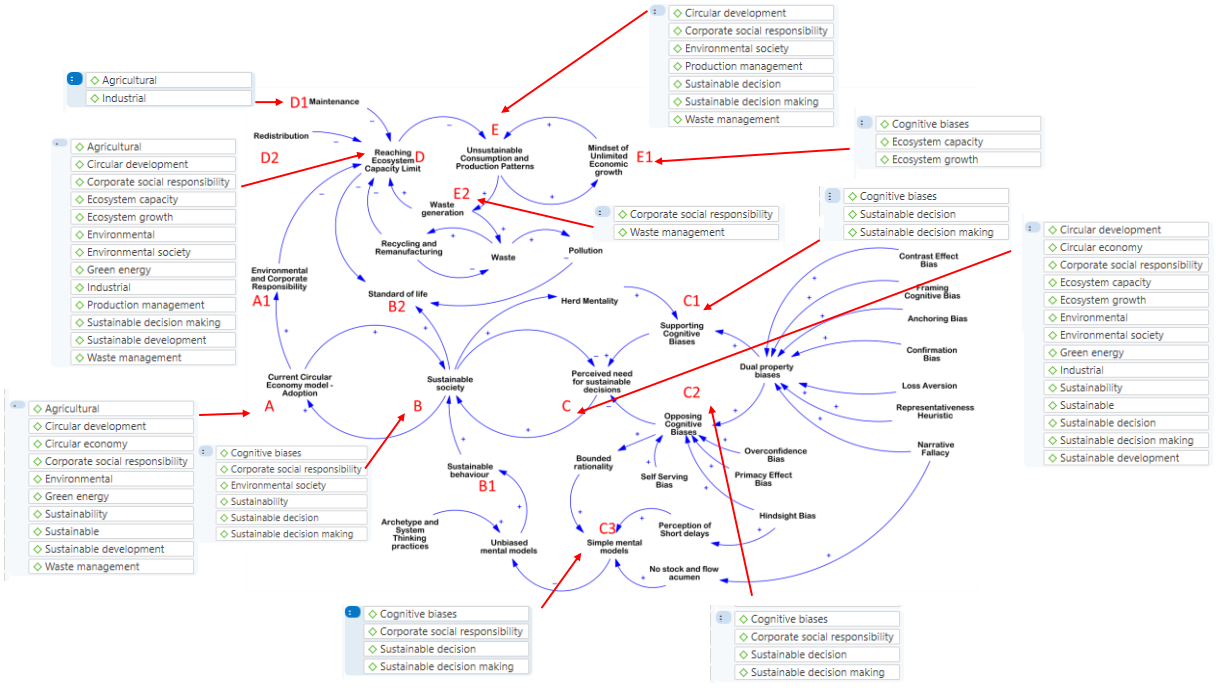

Figure 53. Variable coding for validation of CLD. (van der Linde et al., 2023)

In the CLD, the Corporate Social Responsibility (CSR) variable emerges as the most influential causal factor, closely followed by sustainable decision-making, as seen by the number of grounded connections. Notably, the most robust causal connections exist between coded groups A, B, and C, corresponding to current CE adoption, the aspiration for a sustainable society, and the perceived necessity for sustainable

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decisions, as seen by the shared grounded code connections. Conversely, the weakest causal links are observed in coded groups D and E, representing ecosystem capacity limits and unsustainable consumption and production patterns, aligning with the limited literature on these topics. Within the CLD, the production management category exhibits the least pronounced causal effects among the respective codes. See Appendix G – Model Development 4 – Atlas.ti screenshots for more information on the analysis.

The validated causal relationships can provide valuable insights for further refinement in this study.

This response to RQ3, "How greatly do biases influence the need for sustainability in the CE?" highlights the varying degrees of influence that different factors have on the need for sustainability within the CE. See Section 1.6 for all the RQs. Specifically, Figure 53 underscores the significant impact of CSR and sustainable decision-making, indicating that these factors substantially shape the perceived necessity for sustainability. Additionally, it acknowledges the weaker causal links associated with ecosystem capacity limits and unsustainable consumption and production patterns, suggesting that these factors may have less pronounced effects on driving the need for sustainability. By delineating the strength of causal relationships through grounded coded frequencies among different variables within the CE, this response offers insights into how biases influence the imperative for sustainability, providing a nuanced understanding of the complex dynamics within the CE framework.

4.6. Conceptual Integration of Critical Bias Variables into CE Stakeholder Phases in a Stock and Flow Diagram

The variables used for the SFD simulation are classified into stock, flow, and conversion variables. Stock variables represent current state values derived from previous states, and they can either accumulate or deplete over time (Uehara et al., 2021:285-310; Roos, 2024:253-338). The resources present in the system are also known as state or level variables. In this study, in Figure 55, the stock variable is Biases. Flow variables, or rate variables, control the transformation of resources within the system and change the stock variable over time (Naugle et al., 2024:1-8). They are responsible for directly increasing or decreasing the stock level based on specific rules or equations.

The remaining variables, neither stock nor flow variables, are constants or reference variables, also known as conversion variables. These variables influence the flow by modifying the system's external or internal influences. After identifying and categorising the variables, the next step is to complete the diagram setup. The following section discusses the setup steps and how the variables are further utilised in the modelling process.

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SFDs are essential tools for evaluating the behaviour of specific variables over time. By adjusting variable values and applying mathematical equations, these diagrams can simulate real-world scenarios and predict future states of the system. As discussed earlier, Meadows' concept of "limits to growth" emphasises that any natural system experiencing growth will eventually encounter limiting factors, which can be introduced externally or internally by the system itself (Meadows et al., 2006:397-399).

The initial step in developing the SFD for the limiting growth model is depicted in Figure 54. This SFD will be utilised in future analyses as more quantitative data becomes available in 6.4. The diagram was constructed by identifying and modelling the interactions previously shown in Figure 50.

Several dynamic hypotheses illustrated in Figure 54 include:

- Biases can be supportive and opposing, influencing the need for sustainability and society's consumption and production trends (Vighnesh et al., 2023:990-1007; Winterich et al., 2023:2-9).
- The Earth's resources are finite and subject to biased, unsustainable exploitation (Cornford et al., 2023:2-10; Rockström et al., 2023:102-111).
- The performance of a sustainable society is shaped by long-term goals associated with sustainable models such as the CE framework (Cagno et al., 2023:55-71; Chabowski et al., 2023:1-9).
- Expectations within the CE framework are influenced by societal perceptions, and gaps in sustainable performance are linked to the perceived need for sustainability (Camilleri et al., 2023:1-18; Amicarelli and Bux, 2023:1-16).

This study primarily investigates the effects of biases. Therefore, the limits to growth loop, as seen in Figure 55, was selected for further simulation. This diagram is capable of its fusion of stock and flow dynamics with cognitive bias variables, illustrating how biases accumulate and impact the sustainability trajectories within CE systems.

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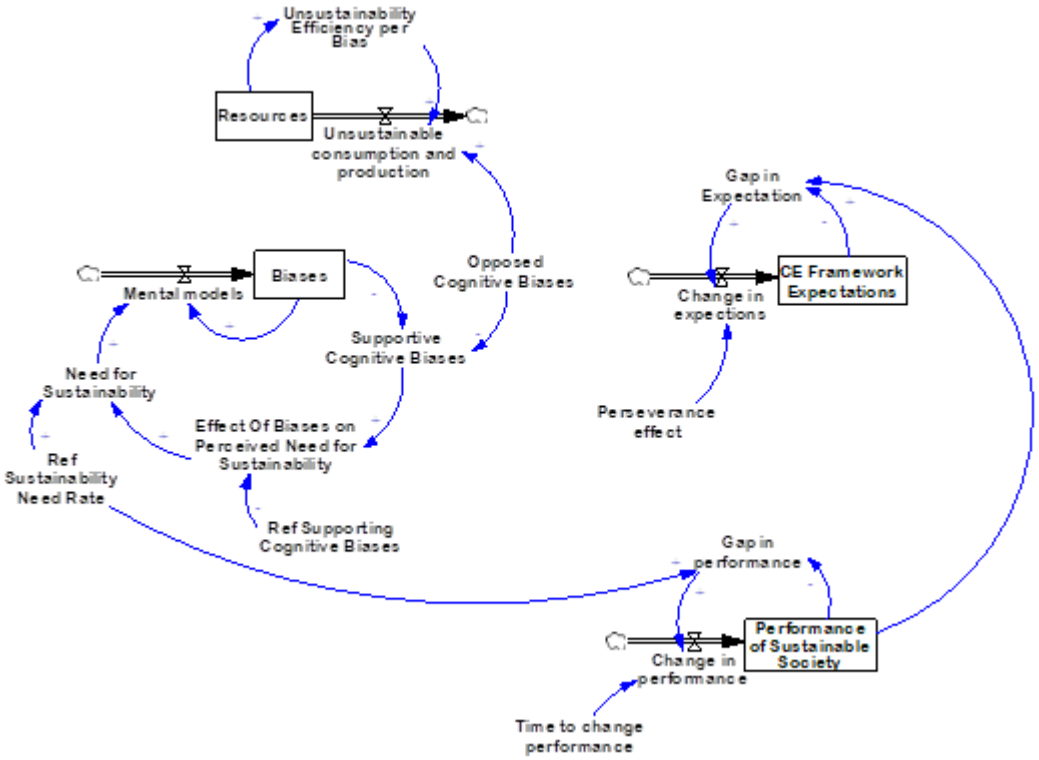

Figure 54. Formulating a conceptual stock and flow diagram for the influence of biases on sustainability. (van der Linde et al., 2023:1-11)

The SFD is novel in its adaptation of the 'Limits to Growth' model to specifically address the impact of cognitive biases on sustainability within the CE, offering a nuanced understanding of how feedback loops and thresholds operate in biased decision-making.

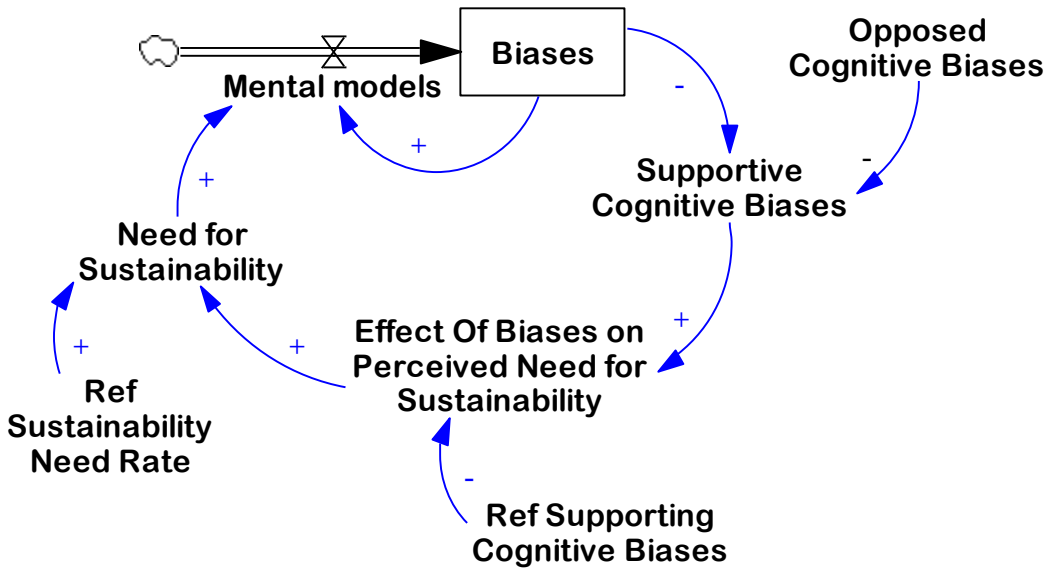

Figure 55. A "limits to growth" stock and flow diagram of the bias influences on sustainability. (van der Linde et al., 2023:1-11)

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4.7. Simulation of Conceptual CE Framework with Different Bias Influences

The reference sustainability need rate is chosen as an arbitrary constant of 0.10, and the reference supporting cognitive biases is chosen as 1.0 for illustration purposes at this stage of the research.

In Figure 55, biases are depicted as the stock with a single inflow, influenced by the mental models of individuals in society. These mental models are a product of the perceived need for sustainability and the number of biases affecting the individual. The perceived need for sustainability is calculated using the reference sustainability rate and the effect of biases, as outlined in equations (1) and (2):

$$Need\ for\ Sustainability = Reference\ Sustainability\ Rate \times Effect\ of\ Biases\ on\ Perceived\ Need\ for\ Sustainability \quad (1)$$

$$Effect\ Of\ Biases\ on\ The\ Perceived\ Need\ For\ Sustainability = Supportive\ Cognitive\ Biases / Reference\ Supporting\ Cognitive\ Biases \quad (2)$$

When the biases equal the opposing cognitive biases, the supportive biases become zero, as shown in equation (3):

$$Supportive\ Cognitive\ Biases = 1 - (Biases / Opposed\ Cognitive\ Biases) \quad (3)$$

This indicates that all influencing biases are negative, resulting in no further perceived need for a sustainable society. Further simulation data on this SFD is provided in the next section. The model development is discussed in Chapter 3.3.3.

Vensim software was utilised to simulate this initial system's behaviour over time, representing real-world decision-making within the model. The simulation used a step increment of 0.25 months, with initial and final values set at 0.00 and 100.0, respectively. For illustration, auxiliary variables and arbitrary constants were used to evaluate the behaviour under different conditions. The model equations were embedded into the Vensim model, following a sequence from supportive cognitive biases to mental models. Key findings of the study include identifying bias influences on a sustainable society, which can be positive or negative. The initial significant result was obtained from interpreting the CLD, where bias influences were shown across several causal loops, including waste generation, sustainable behaviour, and simple mental models. The qualitative CLD was further developed into an SFD for simulation purposes. See Appendix J – Vensim simulations for more information.

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The second result highlighted the need for supportive (positive) cognitive biases to change the mental models of society. The results, illustrated in Figure 56, demonstrate that supportive cognitive biases are essential for altering societal mental models. The horizontal axis represents time in months, and the vertical axis shows units per month for all graphs.

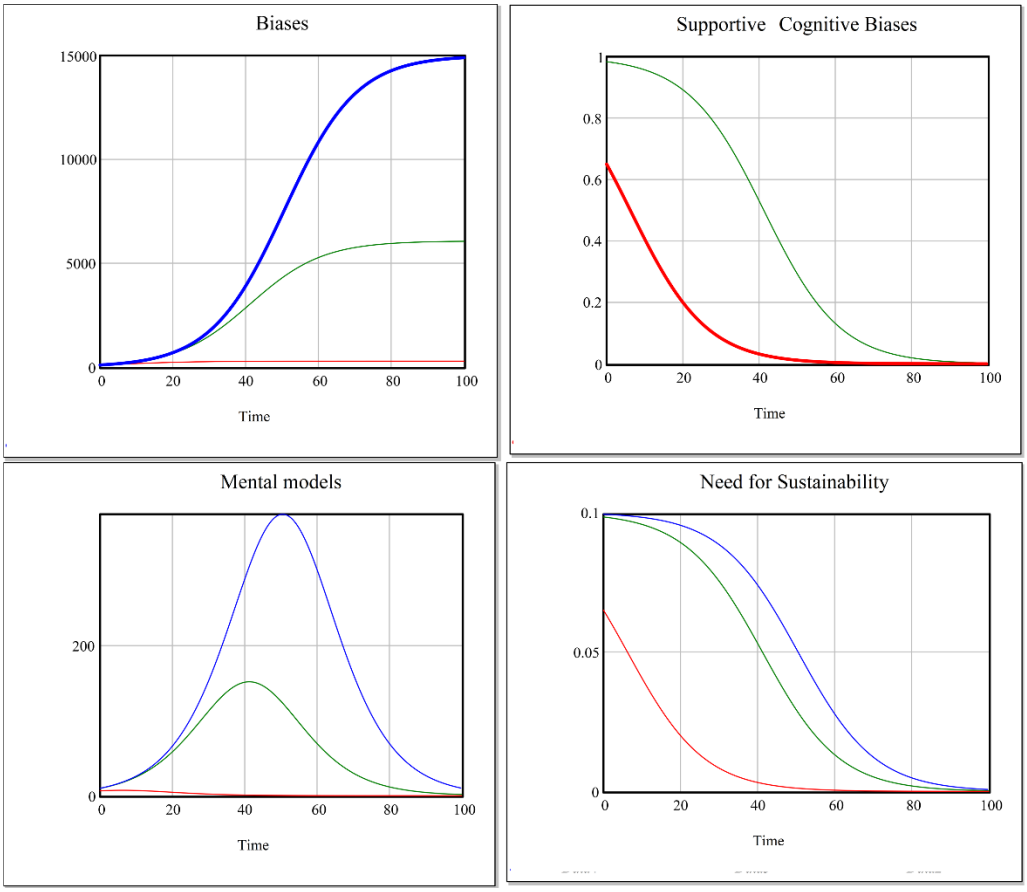

Figure 56. Limits to growth stock and flow diagram simulation outputs of the bias influence on sustainability

In the study's sensitivity analysis, the model or decision-making process is evaluated with varying values for one or more variables to observe how the results change. This approach helps decision-makers assess the robustness of their assumptions and identify which inputs most significantly impact the outcomes. Figure 56 illustrates different datasets used in the simulation. The top blue lines in each graph represent the system's behaviour when supporting biases are at their maximum, the middle green lines show the behaviour with initial model values, and the bottom red lines depict the system when supporting biases are at their minimum.

The graphs, examined clockwise from Figure 56, provide insights into the system model's dynamics.

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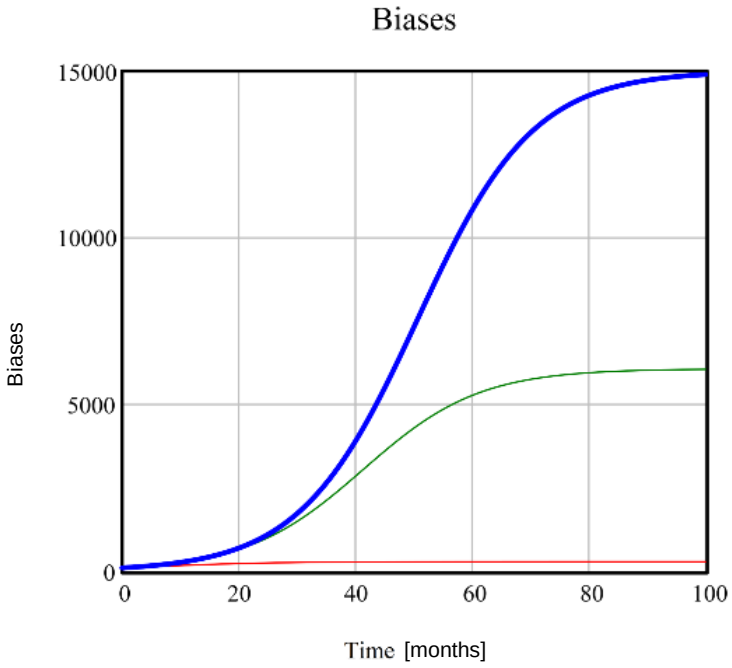

Figure 57. Limits to growth stock and flow diagram simulation outputs with auxiliary data - Biases

The first graph in Figure 57, showing the biases (stock), exhibits s-shaped growth typical of the limits-to-growth model, with exponential growth initially, followed by a change in behaviour at the inflexion point. As the bottom red line shows, when opposing biases reach zero, simple mental models transform into sustainable-holistic ones.

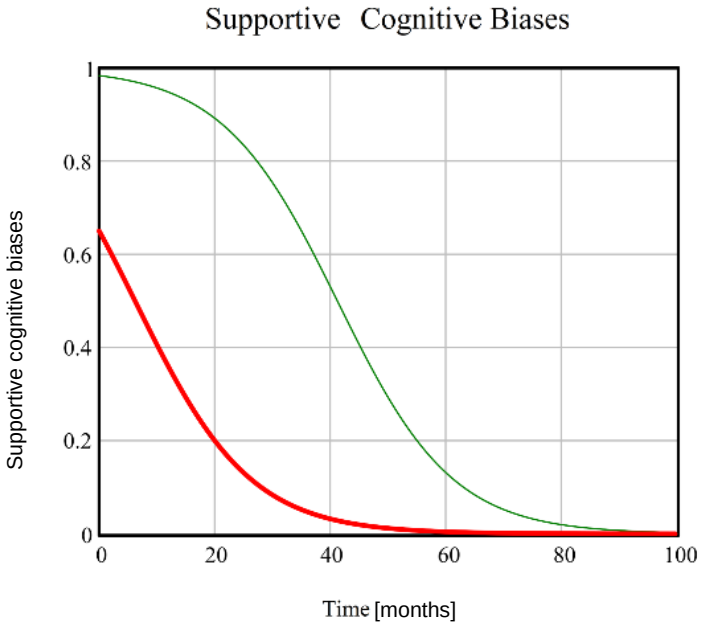

Figure 58. Limits to growth stock and flow diagram simulation outputs with auxiliary data - Supportive Cognitive Biases

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The second graph in Figure 58, depicting supportive cognitive biases, mirrors the stock graph: supporting biases are highest when the stock is lowest, reflecting the interplay between supporting and opposing biases.

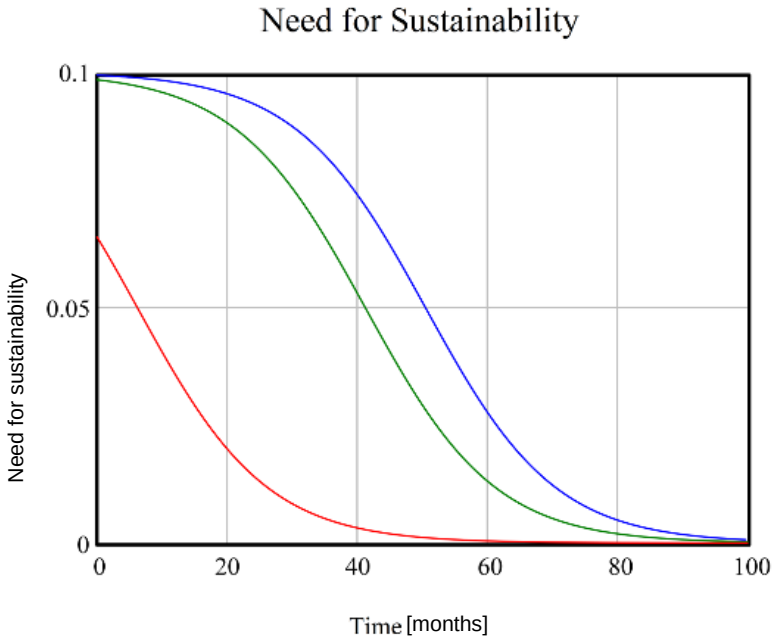

Figure 59. Limits to growth stock and flow diagram simulation outputs with auxiliary data - Need for Sustainability

The third graph in Figure 59, driven by the effect of biases, captures the need for sustainability based on Equation (1). A decrease in supporting biases causes the system to plateau when opposing biases surpass them.

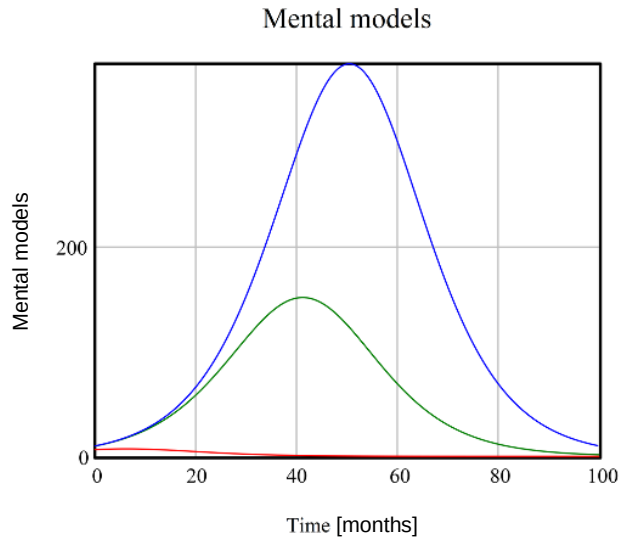

Figure 60. Limits to growth stock and flow diagram simulation outputs with auxiliary data - Mental Models

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The fourth graph in Figure 60 shows the mental models of society, which follow a bell curve, indicating exponential growth to a peak followed by a decline. This decline suggests that biases eventually cease to be influenced by mental models, an unintended consequence explained by the 'business-as-usual' effect, as stated by Meadows et al. (1972:).

The diagrams in Chapter 4 illustrate how biases significantly influence the need for sustainability in the CE by demonstrating the dynamic interplay between supporting and opposing biases and their effect on societal mental models and perceived sustainability needs, answering RQ3. The sensitivity analysis highlights how changes in bias levels can either enhance or diminish the perceived urgency for sustainable practices, directly impacting the adoption of CE principles. This SFD is simulated with survey results in Chapter 6.4.

4.8. Conclusion on Concepts

Figure 57 gives the overall context of these concepts in this section. The Conceptual Model section is part of the first four main DSR stages and the first few sub-cycles. In the following sections, the Evaluation and Conclusions are done with the help of another subcycle.

In conclusion, the conceptual systems model articulated herein offers a framework for systematically identifying and understanding biases. By incorporating thematic content analysis, this model enables the detection of patterns and themes indicative of bias across diverse contexts. Furthermore, it emphasises the interaction between external factors such as culture, socio-economic influences, and institutional policies with individual cognitive processes, thereby shaping decision-making outcomes. The models' relevance extends significantly within the DSR methodology, where the development phase transitions theoretical constructs into practical, actionable solutions. This phase is pivotal, as it refines and tests ideas, ultimately yielding strategies that address real-world problems.

In a world where human interactions and organisational dynamics are constantly evolving, achieving impartiality and objectivity in decision-making is a critical yet challenging goal. Whether obvious or subtle, biases often infiltrate our judgments and actions, resulting in inequities. As societies increasingly value inclusivity and fairness, the ability to comprehend and counteract bias is essential. This model not only aids in recognising bias but also serves as a tool for fostering more equitable and fair practices across various domains, from social justice to corporate governance.

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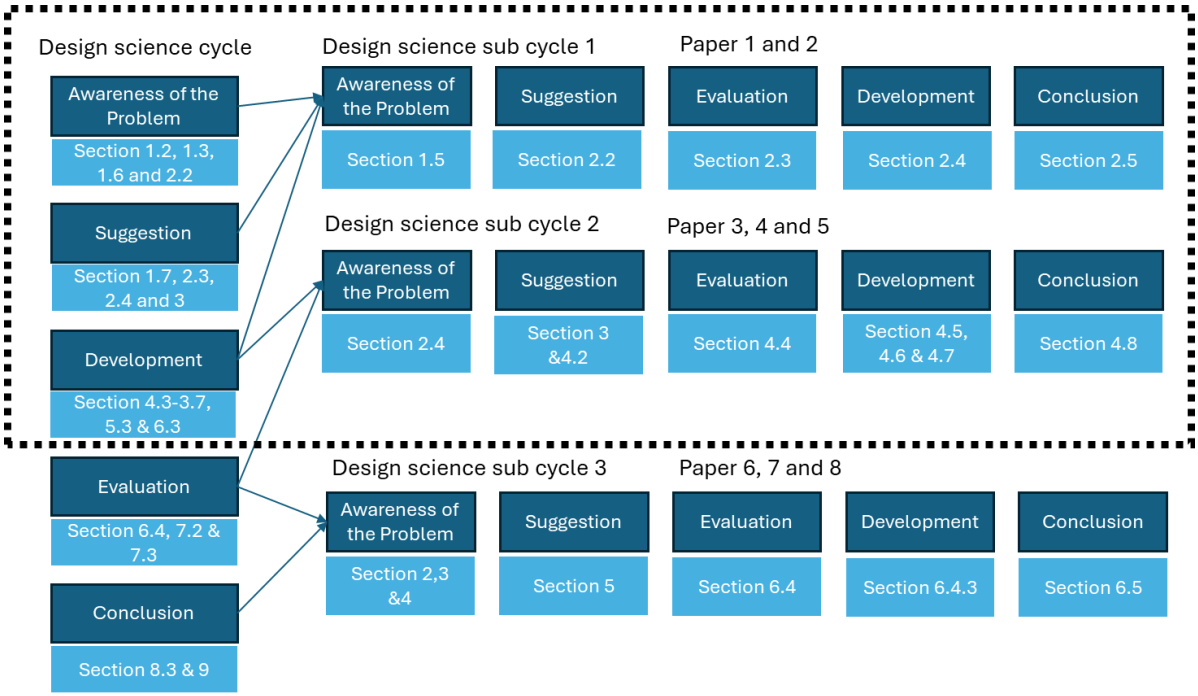

Figure 61. A conceptual model section within the DSR methodology

The chapter concludes with a tangible conceptual model, setting the stage for further development and refinement in subsequent chapters. It demonstrates the creative proposal of a novel solution based on the DSR methodology. Developing the conceptual model is a research process where every iteration and adjustment contributes to creating a scientifically validated artefact.

The model developed in this research is both tangible and conceptual, reflecting its dual purpose of providing a theoretical framework while also offering practical applications. Here's why:

- Tangible aspects: practical implementation: The model is tangible because it can be implemented and tested in real-world scenarios, such as decision-making processes, simulations, or experimental settings. It is built with specific parameters, data, and algorithms that allow it to produce measurable outputs. This makes the model operational, enabling stakeholders to apply it in various domains like corporate governance or cognitive bias analysis, thus validating its real-world utility.
- Conceptual aspects: theoretical framework: Conceptually, the model is designed to represent and analyse complex interactions—such as cognitive biases influencing decision-making—within a structured theoretical framework. It draws upon established theories in psychology, decision science, and governance and abstracts these into a systematic representation that helps explain relationships between key variables.
- Systematic understanding: As a conceptual model, it serves to provide a clearer understanding of how different components, such as biases or governance

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principles, interact within a system. This abstract representation helps users visualise complex processes that may not be easily measurable or observable but are critical for decision-making and strategy formulation.

The conceptual model chapter lays the theoretical foundation for understanding the key interactions and relationships central to this research, particularly focusing on cognitive biases and their influence on decision-making processes. By abstracting these interactions into a systematic framework, the conceptual model provides a structured lens through which the research questions are examined. This framework highlights the critical factors and variables involved, guides the formation of hypotheses, and identifies areas that require empirical investigation. The clarity and structure offered by the conceptual model are essential in framing the scope of the study, ensuring that each component aligns with the overarching research objectives.

Building on this foundation, the research design and methodology chapter operationalises the conceptual model, translating its theoretical constructs into measurable variables and testable procedures. The DSR methodology, which underpins the entire research, is applied to guide the model's iterative development, testing, and refinement. In this way, the conceptual model informs the research design by providing the necessary framework for selecting appropriate methods, data collection strategies, and analytical techniques. Through this iterative process, the research design ensures that the theoretical insights from the conceptual model are tested and validated, ultimately producing a robust and reliable set of findings that contribute both to theory and practice.

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5. Research Design and Methodology

Chapter 5 outlines the overarching research methods employed in the study. It details the research strategy, DSR methodology, and survey processes. This section fits into the DSR framework of the thesis, as shown in Figure 62.

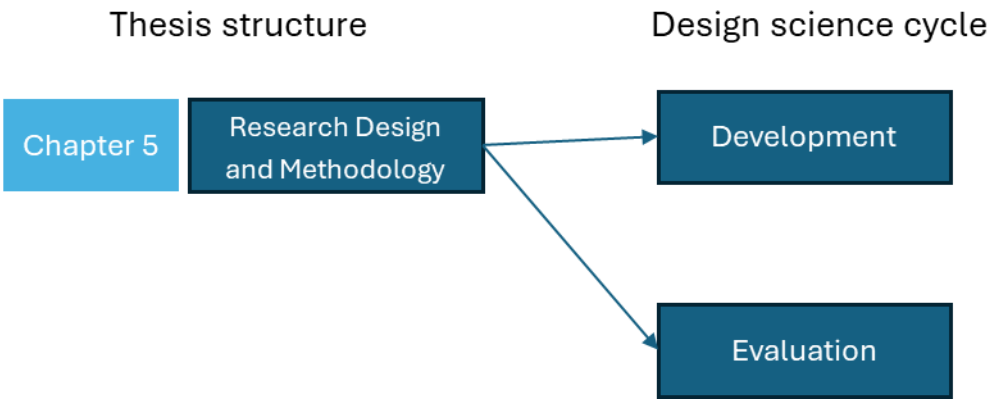

Figure 62. Design Science Research Framework - Chapter 5

Think of the process of building a high-speed train system. The engineering is precise, but the project's success hinges on understanding how potential passengers perceive safety, convenience, and cost—factors often influenced by cognitive biases. In this chapter, the research outlines a research methodology that, like designing a train route, captures both the technical and mental dimensions of decision-making in the CE. The study employs the DSR methodology to iteratively refine the system model and our understanding of these biases. The DSR and conceptual model development research methods were discussed in Chapters 2, 3 and 4. Just as the train's success depends on anticipating human behaviour, our approach ensures that our framework is relevant, integrating human behaviour into the core of SE.

5.1. Introduction

In this thesis section, the research delves into the foundational pillars underpinning the investigation of bias identification and decision-making influences. Research design and methodology are crucial components of scholarly inquiry, shaping the trajectory of the study and providing the tools to navigate the complex terrain of the research domain. The research aims to ensure the findings' validity, reliability, and generalisability through a thoughtful and systematic approach while exploring the multifaceted intricacies that characterise bias and decision-making phenomena. This is done through utilising SE tools such as CLDs and SFDs.

The research design serves as the blueprint for the study, outlining the overall structure, scope, and objectives that guide the investigation. By carefully defining the research questions and hypotheses, the research seeks to address the fundamental inquiries that drive the exploration of bias identification and decision-making

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influences. Moreover, selecting appropriate data sources, sampling techniques, and data collection procedures will allow the researcher to gather rich and relevant information to illuminate the research topic's nuances and complexities.

The study has adopted a comprehensive and multidisciplinary approach to the research methodology. By drawing from various fields such as SE, sociology, organisational behaviour, and cognitive science, the research aims to understand the factors contributing to biased decision-making in different contexts. Thematic content analysis mapping emerges as a powerful tool within the methodological toolkit, enabling the researcher to systematically analyse textual data to identify recurring patterns and themes from surveys that illuminate bias and its influences on decision-making processes. This is explained in Chapter 3.

As the researcher embarks on this journey, the researcher is committed to upholding the principles of ethical research conduct, ensuring the confidentiality and anonymity of the participants while obtaining informed consent. By adhering to ethical guidelines, the researcher strives to maintain the study's trust and integrity, fostering an environment of openness and collaboration.

5.2. Research Strategy

An exploratory study will be used to explore the phenomenon of cognitive biases, and a comparative analysis will be used to compare the CE phases with the identified biases.

Inductive theory building will be used in the study's research process, concluding several research processes to form a general theory around sustainable decision-making.

The exploratory study involves a preliminary investigation into the phenomenon of cognitive biases. This phase allows the researcher to understand the various cognitive biases that may be at play in decision-making processes related to sustainability and the CE. Through literature review, case studies, and expert interviews, the researcher identifies and explores different cognitive biases individuals and organisations may exhibit when making sustainable decisions. This qualitative phase will generate insights and hypotheses about the relationships between cognitive biases and sustainable decision-making.

The comparative study is designed to compare the identified cognitive biases with the different phases of the CE. The CE is a systems-based approach that seeks to design out waste and promote sustainable resource management throughout a product's life cycle. By comparing the cognitive biases with the specific phases of the CE (e.g., design, production, consumption, and end-of-life), the researcher aims to understand

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how biases may influence decision-making at each stage. This phase involves analysing data from different sources, including case studies, surveys, and experimental studies, to identify potential patterns and connections between cognitive biases and decision-making within the CE framework.

Inductive theory building is the overarching research process that guides the study. It involves developing theories and concepts based on empirical data and observations rather than starting with pre-existing theories and hypotheses. In this study, the researcher will gather data from the exploratory and comparative phases, analyse the findings, and derive general theories and insights about sustainable decision-making in the context of cognitive biases and the CE. The focus will be on understanding how cognitive biases interact with specific phases of the CE and how these biases may hinder or facilitate sustainable decision-making.

Using an exploratory approach, the researcher can gain a nuanced understanding of the complex cognitive biases that influence sustainable decision-making. The comparative study then allows for a deeper exploration of how these biases manifest in the specific context of the CE. The goal of inductive theory building is to formulate a general theory that contributes to the existing knowledge on sustainable decision-making, providing valuable insights for practitioners, policymakers, and researchers seeking to promote sustainability within the CE framework.

This approach is closely related to SD, a methodology designed to understand and model the behaviour of complex systems over time. Cognitive biases influencing sustainable decision-making can be seen as dynamic variables interacting within a broader system, such as the CE. Using SD, feedback loops are explored—reinforcing and balancing—that are influenced by these biases, which may either promote or hinder sustainable practices. For instance, biases like short-term thinking or status quo bias could act as reinforcing loops that perpetuate unsustainable behaviour, while other interventions, such as educational campaigns, could serve as balancing loops to mitigate such effects. This systemic understanding allows for a more comprehensive exploration of how cognitive biases evolve and influence the long-term sustainability outcomes within the CE.

In addition, SD complements the inductive theory-building approach by providing a framework to model and simulate how different biases interact over time and across various contexts. By integrating feedback loops and causal relationships within the CE, dynamic tests on how cognitive biases affect decision-making processes and outcomes are done. This is particularly valuable for generating insights about leverage points—specific areas within the system where interventions could lead to significant improvements in sustainability. Ultimately, SD enriches the exploratory and comparative study by providing a temporal and systemic perspective, helping to

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transform conceptual understanding into a more robust, generalisable theory for sustainable decision-making within the CE.

5.3. Research Methodology

The Research Methodology section of this thesis presents a comprehensive framework for investigating the phenomenon of bias identification and decision-making influences within the context of sustainable practices and the CE. This section outlines the chosen research methods, data collection techniques, and analytical approaches that were employed to address the research questions and achieve the research objectives outlined in the study, as discussed in 1.5 and 1.6.

In Table 22, the research methods and design are discussed.

Table 22: Research design and methods

Research method	Data collection	Data type	Application*	Data analysis	Outcome*
Literature Review and Systems Dynamics	Secondary	Qualitative	RQ1, RQ2 and RQ3	Systems Methodologies and thematical analysis	RO1
Surveys: Stratified sampling Focus Groups and Systems Dynamics	Primary	Quantitative	RQ4 and RQ5	Statistical analysis	RO2

**Note: RQ-Research Question, RO-Research Objective*

The first component of the research methodology involves a systematic literature review. This secondary data collection method will draw upon various scholarly sources, academic journals, and reputable publications to gather existing knowledge on cognitive biases, sustainable decision-making, and the CE. By utilising a qualitative approach, the literature review aims to synthesise and critically analyse prior research findings, allowing for a comprehensive understanding of the subject matter and providing a robust theoretical foundation for the study. The literature review addressed RQ1, RQ2, and RQ3, focusing on exploring the presence and effects of cognitive biases in the context of sustainability.

The second data collection method comprises surveys to gather primary data from individuals. Stratified sampling will ensure representative samples from different stakeholder groups, enhancing the study's generalisability. Employing a quantitative approach, the surveys will be structured to explore specific aspects of bias identification and decision-making influences within the CE. RQ4 and RQ5 will be addressed through the survey data, allowing for a comprehensive understanding of the perspectives and behaviours of stakeholders in sustainable decision-making

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processes. See Table 36 for a summary of the answers to all the RQs and Section 1.6 for the discussion on the RQs.

Qualitative and quantitative analytical methods will be used to analyse the data obtained from the literature review and the surveys. For the literature review, a thematic analysis identified recurring themes and patterns related to cognitive biases in sustainability and the CE, aligning with RO1. In contrast, the survey data underwent statistical analysis, including descriptive statistics and inferential tests, to quantify relationships and trends, contributing to RO2.

The Systems Methodology referenced in Table 22 above has been used recently to evaluate the COVID-19 crisis by El-Taliawi and Hartley (2021:104-107), and it includes the following stages, very similar to the SSM discussed in 2.4.2:

- Stages 1 and 2 attempt to build the best possible picture of the situation.
- Stage 3 aims to describe the nature of the chosen system.
- Stage 4 produces conceptual models of the defined system.
- Stage 5 compares the conceptual model with the actual situation to generate debate with the stakeholders.
- Stage 6 outlines possible changes that are desirable and feasible.
- Stage 7 involves acting based on stage 6.

SSM has been successfully used by several PhD students in the System Engineering field at the University of Pretoria (Watkins, 2000:266; Scribante, 2019; Lefike, 2021). The theses of these students were reviewed as part of the literature review and concept mapping for this study. The philosophy to follow in this study is a critical realism ontology, with an interpretive personal epistemology as described by Walwyn (2019:56-63). The survey questions was validated for content and coding factors before the final iteration was sent out to respondents, as defined by Soosalu et al. (2019:2-15).

This is a socio-technical study, where mental models and dynamic systems modelling are used to understand and improve decision-making in the CE. In Table 23, a proposed set of survey questions is illustrated to indicate that the scope is not psychology-based but rather technically sustainably based, similar to the questionnaires used in evaluating sustainable living by Triantafyllidou and Zabaniotou (2022:113-139). To reiterate the previous statement, this study is a socio-technical study, not a consciousness or mindset study. See Appendix B – Survey questions extracted from Jotform for the final revision of the Survey questionnaire.

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Table 23. Example of possible survey questions for this study

Survey question	Likert scale / options	Reason for question
Employment	Open space for job description	Stakeholder identification in the CE
How informed are you about sustainability issues?	Likert scale	Assess sustainability consciousness
Do you believe climate change is real?	a) Yes b) No	Identify inattentional blindness cognitive bias
Where will be the most crucial place to adopt a more sustainable means?	a) Personal lifestyle b) Product manufacturing c) Mining d) Farming e) Food	CE phase identification for better decision-making
Would you spend more money to buy repaired, re-used or recycled products than new ones?	Likert scale	Identify self-serving cognitive bias
Which items do you recycle, repair or re-use in your personal life?	Open space	CE phase identification for better decision-making
Which items do you recycle, repair or re-use in your professional life?	Open space	CE phase identification for better decision-making
Do you agree with the following view: Is it imperative to reduce the use of fossil fuels in our daily lives by increasing the demand for sustainable products?	Likert scale	Identify confirmation cognitive bias.
How important is it for you that society follows environmentally friendly practices?	Likert scale	Identify the availability of cognitive bias
Do you agree with the following view: There is no proper way to change the public's awareness of the need to establish a more sustainable reality?	Likert scale	Identify hindsight cognitive bias.
Which factors will convince you to buy/use sustainable products?	a) Green information availability b) Green information accuracy c) Reduced cost d) Re-usability e) Better quality	Causal factor analysis
Are you willing to change your habits to be more sustainable?	a) Yes b) No	Stakeholder flexibility and cognition assessment

5.4. Research Surveys

The Research Surveys section of this thesis represents a pivotal phase in investigating bias identification and decision-making influences within the context of sustainability and the CE. As a primary data collection method, surveys are a powerful tool to gain insights from stakeholders and individuals directly involved in sustainable decision-making. This section presents the details of the survey design, data collection

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procedures, and analytical approaches employed to address the research questions and achieve the objectives. See Section 6.2 and 6.3 for a detailed discussion on sample size.

By adopting a stratified sampling technique, the survey aims to ensure the representation of diverse stakeholder groups, encompassing consumers, policymakers, industry experts, and other relevant participants. This strategic approach allows for a comprehensive exploration of how cognitive biases influence decision-making across distinct strata, providing valuable insights into the intricacies of sustainable practices and their alignment with the CE.

The quantitative nature of the survey allows for the systematic analysis of responses, facilitating the identification of trends, patterns, and associations. Statistical analysis will be applied to interpret the survey data, enabling quantitative insights into the relationships between cognitive biases and sustainable decision-making practices.

This section also outlines the ethical considerations of survey research, focusing on informed consent, confidentiality, and data protection. Ensuring the privacy and anonymity of participants is paramount to fostering a climate of trust and cooperation, encouraging candid responses that enrich the research findings.

Through the Research Surveys section, this study explores stakeholders' perspectives, behaviours, and decision-making processes within the CE. The research aims to generate meaningful data that contributes to a more informed and equitable approach to sustainable decision-making by employing a robust survey design and methodology. Ultimately, this section plays a crucial role in exploring bias identification and decision-making influences, aligning with the broader goal of promoting sustainable practices within the CE framework.

A practical approach to ensure a robust survey design and methodology was followed. The research clearly defined its objectives at the outset, aligning them with the study's research questions and overarching goals. This step provided a focused direction for developing the survey and ensured the research methods captured relevant data to address the research inquiries effectively.

To identify the target population, the researcher included consumers, policymakers, industry experts, and other stakeholders within the CE. Understanding the characteristics and demographics of the target population was crucial for appropriate sampling and ensuring the findings' generalisability. The research adopted stratified sampling and divided the target population into distinct strata based on relevant characteristics, such as occupation, industry, or expertise. This approach gave the

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research a diverse and comprehensive sample, ensuring representation from various stakeholder groups.

Crafting a comprehensive questionnaire was an essential aspect of the survey design. The research included both closed-ended and open-ended questions in the questionnaire. Closed-ended questions facilitated efficient data collection and were analysed quantitatively, while open-ended questions allowed participants to provide in-depth responses, contributing to a richer understanding of their perspectives.

Before administering the survey, the researcher conducted a pilot test with a small sample to identify issues with question clarity, survey flow, or response options. Piloting helped the researcher fine-tune the survey instrument and ensured participants could easily understand it, enhancing the overall data quality.

To enhance the validity and reliability of the survey data, the researcher used established scales and validated measures for critical constructs. The research also included attention-check questions to identify and eliminate responses from inattentive or insincere participants, further ensuring the integrity of the data.

Throughout the survey process, ethical considerations were a priority. The researcher obtained informed consent from participants and ensured their confidentiality and privacy. The researcher communicated the purpose of the study and emphasised the voluntary nature of participation to foster trust and cooperation among the participants.

The ethics approval form is attached in Appendix A – Ethics approval, and the survey is in Appendix B – Survey questions extracted from Jotform.

Data collection was implemented using online surveys, considering the accessibility and preferences of the target population. The online platform allowed for efficient data gathering and provided a convenient means for participants to respond.

Following this practical approach to survey design and methodology, the researcher collected robust and reliable data, gaining valuable insights into bias identification and decision-making influences within sustainability and the CE. The survey findings contributed to a comprehensive understanding of the research domain and supported the development of evidence-based recommendations for promoting sustainable practices.

5.5. Conclusion

In summary, this Chapter on research design and methodology lays the groundwork for investigating bias identification and decision-making influences. Through a systematic and interdisciplinary approach, the research sheds light on the complex interplay of factors that shape human judgments and decisions to contribute to a more

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equitable and informed society. By adopting a research design and employing robust methodologies, the research endeavours to explore the multifaceted aspects of the research topic while upholding the highest standards of scientific rigour and ethical practice.

The outcome of the research methodologies discussed will be a rich dataset that enables a comprehensive exploration of the complex relationships between cognitive biases and decision-making influences within the context of sustainability and the CE. By employing a mixed-methods approach, this study seeks to provide a multi-faceted understanding of the factors that shape sustainable decision-making, offering valuable insights for practitioners, policymakers, and researchers seeking to promote sustainable practices in diverse contexts. Through a comprehensive research methodology, this thesis aims to contribute to the existing body of knowledge, fostering a more informed and equitable approach to sustainable decision-making in the CE.

This chapter provides a comprehensive overview of the research design, preparing the reader for the data presentation and analysis in the following chapters. The structured application of the DSR methodology in designing the research process underscores that each phase of model development and testing is a distinct research activity.

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6. Results

Chapter 6 presents the data gathered through the methods discussed in Chapter 5. It includes a detailed account of the data collection process and a summary of the collected data. This section fits into the DSR framework of the thesis, as shown in Figure 63.

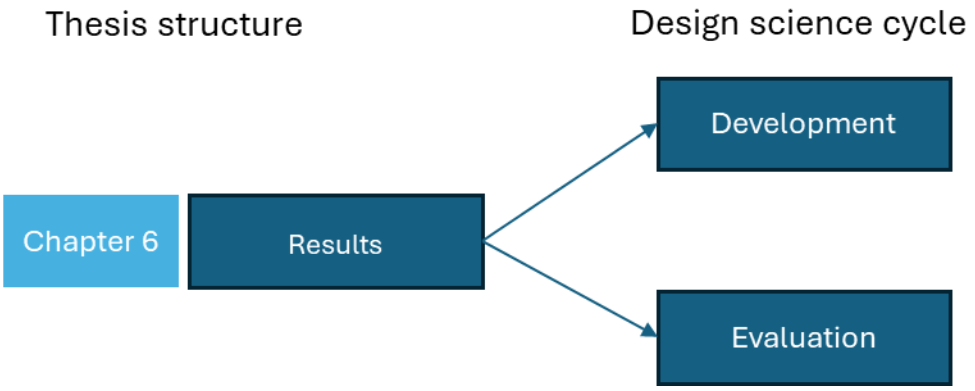

Figure 63. Design Science Research Framework - Chapter 6

Consider an architect designing a new city park. They create a beautiful layout, but the park could be underutilised if they don't consider how people will use the space—where they prefer to walk, gather, or relax. Similarly, in this chapter, the results presented continuously link back to the central narrative: integrating SE with cognitive biases to enhance decision-making in the CE. The research demonstrates how this approach, like designing a park with both aesthetics and user behaviour in mind, leads to more sustainable outcomes. The study also highlights instances where ignoring these biases has hindered sustainability efforts, reinforcing the need for a framework that fully considers the human element.

6.1. Introduction

The Results chapter of this thesis represents a significant milestone in exploring bias identification and decision-making influences within sustainability and the CE. In this section, the researcher presents and analyses the data collected through a robust survey and other relevant sources, comprehensively examining the research findings. The results unveiled in this section are instrumental in addressing the research questions and achieving the research objectives outlined in the study. The results of the data gathering and analysis are discussed in this section with the results of the SD model simulations discussed in Section 8.

Through meticulous data analysis and interpretation, this section sheds light on the complex relationships between cognitive biases, sustainable decision-making practices, and the different phases of the CE. Drawing upon quantitative and qualitative

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methods, this section offers a multi-faceted understanding of the factors influencing decision-making processes within sustainability.

The quantitative analysis of survey data enables a systematic exploration of the prevalence and impact of cognitive biases among various stakeholder groups. Descriptive statistics provide insights into the patterns and associations between biases and decision-making outcomes, offering empirical evidence to support the study's conclusions.

In parallel, the qualitative analysis of open-ended survey responses and thematic content analysis of relevant textual data enrich an understanding of the underlying complexities and motivations guiding sustainable decisions. This approach uncovers participants' nuanced perspectives and experiences, providing valuable context to complement the quantitative findings.

The key findings are presented clearly and coherently, organising the information logically and structured. The presentation of data is supported by tables, graphs, and qualitative excerpts, facilitating a comprehensive visualisation and interpretation of the research outcomes.

Furthermore, this section will address any unexpected findings or limitations encountered during the study, acknowledge the challenges, and provide valuable insights for future research endeavours.

6.2. Data Gathering Process

The selection of an appropriate sample size is a critical consideration in survey research, especially for a PhD study seeking to investigate the intricacies of bias identification and decision-making influences within the context of sustainability and the CE. In this study, the sample size of approximately 80 respondents is deemed adequate and justified through stratified sampling, an effective technique that ensures representative samples from different stakeholder groups (Kotrlik and Higgins, 2001:43-50)

Stratified sampling partitions the target population into subgroups, or strata, based on specific characteristics relevant to the research questions. In this case, stakeholders from diverse backgrounds, such as consumers, policymakers, and industry experts, are grouped into different strata. Focusing on a manageable sample size of 80 respondents ensures that each stratum is appropriately represented, resulting in a more balanced and insightful data collection process.

The sample is sufficient for achieving statistically meaningful results while allowing for in-depth qualitative analysis. This approach aligns with the principles of mixed-

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methods research, which seek to integrate quantitative and qualitative data to provide a comprehensive understanding of the research topic (Clark, 2019:106-111). Stratification allows for targeted data collection, ensuring that key stakeholders and perspectives are adequately represented in the sample (Lohr, 2000:73-116). By dividing the population into relevant subgroups, the research can account for variations in cognitive biases and decision-making influences within each stratum, resulting in a more nuanced and comprehensive analysis.

Additionally, the sample size of respondents balances practicality and statistical significance. Larger samples can be resource-intensive, increasing costs and time constraints, especially in doctoral research settings. Conversely, a tiny sample may not provide enough data to draw meaningful conclusions or to detect subtle patterns within the data (Krejcie and Morgan, 1970:607-610). This ensures that the research remains manageable, allowing for thorough data analysis and a more focused investigation of the research questions.

Furthermore, stratified sampling reduces the risk of bias in the sample. Ensuring proper representation of various stakeholder groups makes the research findings more likely to be generalisable and applicable to the broader population. This methodological approach contributes to the validity and reliability of the research outcomes, strengthening the overall credibility of the study (DeVellis and Thorpe, 2022:298).

In summary, using stratified sampling with 80 respondents offers a practical and robust approach for this PhD survey study on bias identification and decision-making influences within sustainability and the CE. By capitalising on the benefits of stratified sampling, the research can efficiently explore the complexities of cognitive biases and decision-making across diverse stakeholder groups, ultimately contributing to a more comprehensive and informed understanding of sustainable decision-making practices.

6.3. Data Gathered

Surveys were distributed using Jotform, a versatile online form builder that facilitates the creation and dissemination of surveys. The process involved crafting a user-friendly survey with clear and concise questions tailored to gather the necessary data for our research. This survey was then shared via multiple channels, including email invitations, social media links, and embedded website forms, ensuring a broad reach. The survey attracted 276 views, reflecting the target audience's initial interest and engagement. Out of these 276 views, 79 responses were successfully collected, indicating a response rate of approximately 28.6%. According to industry standards, this response rate is considered good, as typical online survey responses range between 20% and 30%.

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The collection of 79 responses is statistically sufficient to test the hypotheses and conduct simulations for the conceptual model. In survey research, a response rate above 20% is deemed adequate for obtaining reliable data. Moreover, the absolute number of responses (79) provides a robust sample size for analysis, very close to the aim of 80 as mentioned earlier. Statistical power analysis suggests that a sample size of 30-50 is often enough to detect medium to significant effects, depending on the study's design and objectives. Therefore, with the 79 responses, the research has more than enough data points to perform meaningful statistical analyses, validate our hypotheses, and simulate our conceptual model with reasonable confidence. This sample size allows for diverse insights and enhances the reliability and generalisability of our research findings.

The raw data can be seen in Appendix C – Raw data from surveys.

After collecting the survey data, the researcher used suitable statistical analysis techniques to process and interpret the data. The quantitative analysis involved descriptive statistics while the qualitative study involved thematic content analysis to identify recurring patterns and themes.

6.4. Data Analysis

Thoroughly interpreting the survey findings in the context of the research objectives and RQs, the researcher presents the results clearly and concisely in the following sections. The research aims to show enhanced clarity and impact by utilising graphs, tables, and qualitative excerpts. The data analysis within this thesis employs a multifaceted approach grounded in the DSR methodology, integrating both qualitative and quantitative methods to provide a comprehensive understanding of the research problem. The overall link to the research questions and objectives can be seen in Figure 2. The SSM and Bayes theorem explored and validated complex systems and probabilistic relationships. Archetypes and decision ladders were utilised to identify recurring patterns and decision-making processes. The Iceberg model helped distinguish between surface-level events and deeper systemic structures, while the theoretical integrated framework provided a cohesive lens for synthesising various conceptual insights. Atlas.ti facilitated thematic analysis, allowing for systematic coding and categorisation of qualitative data, further linked to conceptual frameworks derived from a thorough literature review.

Incorporating multiple methods, such as the conceptual CLD and Vensim SFD simulation, grounded theory, and systematic literature review, ensured robust data triangulation and validation. Thematic analysis using Atlas.ti, coupled with inductive and deductive coding, was instrumental in identifying core themes and patterns from the survey data, which were then integrated into the CLDs and SFD simulations using Vensim. This iterative process of merging qualitative insights with quantitative

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simulations provided a dynamic and detailed analysis. Focus groups were conducted to validate the CLDs, ensuring their relevance and accuracy.

Additionally, survey data was validated through thematic analysis in Atlas.ti, strengthening the link between conceptual models and empirical data. This comprehensive approach ensured the reliability of the findings and facilitated the development of well-grounded theoretical and practical implications. In Figure 64, a summary of the DSR methodology and data analysis is given.

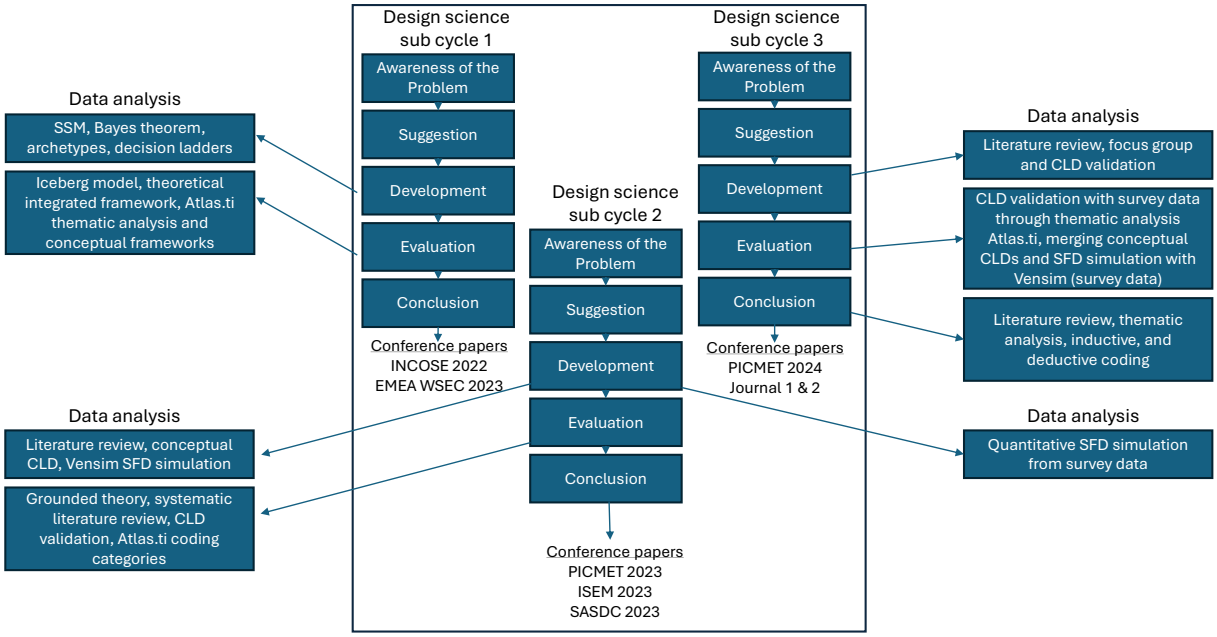

Figure 64. Design Science Research Cycles discussed - Data analysis

The following section elaborates on how the data analysis was done and the outcomes of each method; the conceptual models and how the data analysis methods were applied to them were discussed in Chapter 4.

6.4.1. Integration of Critical Bias Variables into CE Stakeholder Phases in a Stock and Flow Diagram

The conceptual diagram from Figure 54 and Figure 55 has now been adopted with actual data. The methodology employed here aimed to integrate survey data into an SD model and conduct comprehensive analyses to gain insights into the complexities of biases within the CE and enhance the model's behavioural dynamics for real-world applicability. Data analysis software, Atlas.ti, was utilised to analyse the survey data, facilitating the coding and categorisation of responses. This enabled the identification of recurring themes, patterns, and cognitive biases among stakeholders. Through an iterative coding process and constant comparison, the data were organised into a structured format suitable for integration into the SD model. The survey data were coded into biases, sustainability needs, and overall support or opposition to sustainable frameworks such as the CE. Although the middle categories like "neither

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agree nor disagree" were removed from the evaluation, they were included in the survey to ensure valid responses when respondents did not have a strong opinion (Willits et al., 2016:126-139). Document groups were created in Atlas.ti for all option-selection questions and further evaluated by count and category.

The study introduces the concept of BSD as a tool to explore the hidden cognitive biases that influence decision-making within the CE. By drawing inspiration from Malcolm Gladwell's work on subtle societal shifts, the research aims to uncover the complex dynamics that shape the CE. The introduction highlights the importance of understanding these biases, which can significantly impact sustainable decision-making. The study leverages empirical survey data integrated into an SD model to analyse how biases affect CE stakeholders' behaviours, aiming to improve sustainability outcomes by addressing these often-overlooked cognitive influences.

The research concludes that cognitive biases are crucial in shaping societal mental models and the perceived need for sustainability within the CE. The simulations reveal that diminishing opposing biases leads to more sustainable and holistic mental models while increasing such biases hinders progress. The study underscores the need for proactive interventions to mitigate opposing biases and promote supportive ones, thus aligning mental models with long-term sustainability goals. Despite the model's limitations, the findings provide valuable insights for decision-makers and suggest directions for future research, including developing more sophisticated models and practical strategies for bias mitigation.

The coded survey data, enriched with insights on biases and behavioural patterns, were incorporated into the SD model. Previously constructed CLDs and SFD were updated to account for the identified biases and their potential influence on CE decision-making, as shown in Figure 54 and Figure 55. This integration process involved translating qualitative data into quantitative parameters and aligning them with the model's structure. The research identified several dynamic hypotheses, including the profound influence of biases on sustainability, the finite nature of resources, and the performance of a sustainable society tied to enduring goals within sustainable models like the CE framework.

With the survey-augmented SD model in place, simulations were conducted to explore system behaviour under various bias-related scenarios. Atlas.ti-facilitated insights were crucial in setting initial conditions and parameter values for the simulation experiments. These simulations allowed for an assessment of how biases influenced key CE variables, such as adopting sustainable practices. From Atlas.ti, variable data for biases, opposed cognitive biases, supportive cognitive biases, reference supporting biases, and reference sustainability need rates were obtained.

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The powerful capabilities of the Vensim software were leveraged to facilitate a dynamic simulation of the system's behaviour over time, significantly enhancing the reliability of real-world decision-making representations within the model. This approach included embedding all model equations within the Vensim software, forming the backbone of the simulation framework. The evaluation sequence commenced with supporting cognitive biases, followed by the effect variable function, assessing the need for sustainability, and an in-depth analysis of mental models. This methodological approach provided valuable insights into CE dynamics and the potential effects of bias-leveraging strategies, contributing to advancing sustainable practices within this critical economic framework. The results, presented in the subsequent sections, underscore the significant role of supportive cognitive biases in transforming society's mental models and illustrate the mechanisms of the system model.

The simulation was done as follows: The first variable, the perceived need for sustainability, is detailed in Equation (1) below:
(Note that in each section the numbering for the equations restarts at 1, no cross references between section for equations are made throughout this paper)

$$Need\ for\ Sustainability = Reference\ Sustainability\ Rate \times Effect\ of\ Biases\ on\ Perceived\ Need\ for\ Sustainability \quad (1)$$

The reference sustainability need rate, equating to 0.134, was calculated from three survey questions focused on sustainability awareness. The reference supporting cognitive biases, equating to 0.80, was derived from the ratio of the total bias count from fourteen survey questions to the total supportive bias count from the same dataset. Building upon the research, a crucial relationship between biases and their impact on the perceived need for sustainability is established, as summed up in Equation (2):

$$Effect\ Of\ Biases\ On\ The\ Perceived\ Need\ For\ Sustainability = Supportive\ Cognitive\ Biases\ /Reference\ Supporting\ Cognitive\ Biases \quad (2)$$

When biases align accurately with opposing cognitive bias influences, the existence of supporting biases diminishes entirely, as depicted in Equation (3):

$$Supportive\ Cognitive\ Biases = 1 - (Biases\ /\ Opposed\ Cognitive\ Biases) \quad (3)$$

During the simulations, a step increment of 0.25 was employed, starting with an initial value of 0.00 and culminating at a final value of 100.0. These selected parameters

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were instrumental in illuminating the evolution of the model's dynamics. The results in Figure 4 underscore a significant finding: introducing supportive cognitive biases plays a pivotal role in transforming society's mental models.

In the graphical representations, the horizontal axis is labelled as Time (months), while the vertical axis consistently uses the unit of measurement (number/ratio of). The sensitivity analysis conducted in this study subjected the model and decision-making process to various scenarios for one or more variables, aiming to understand how these alterations impact the outcomes. This approach is critical for gauging the resilience of assumptions and pinpointing the variables with the most pronounced influence on the results. Figure 65 provides an overview of the different datasets employed for running the simulation.

Within each graph, a distinct pattern emerges. The top blue lines, representing scenarios with a maximum capacity for opposing biases at a value of 2030 (double the base case value), illustrate one end of the spectrum. The green lines depict the model's starting base values, as discussed in the previous section. Lastly, the red lines, signifying scenarios with minimum opposing biases at almost half the base case value (set at 100), capture the other extreme of the spectrum. See Appendix J – Vensim simulations for more details.

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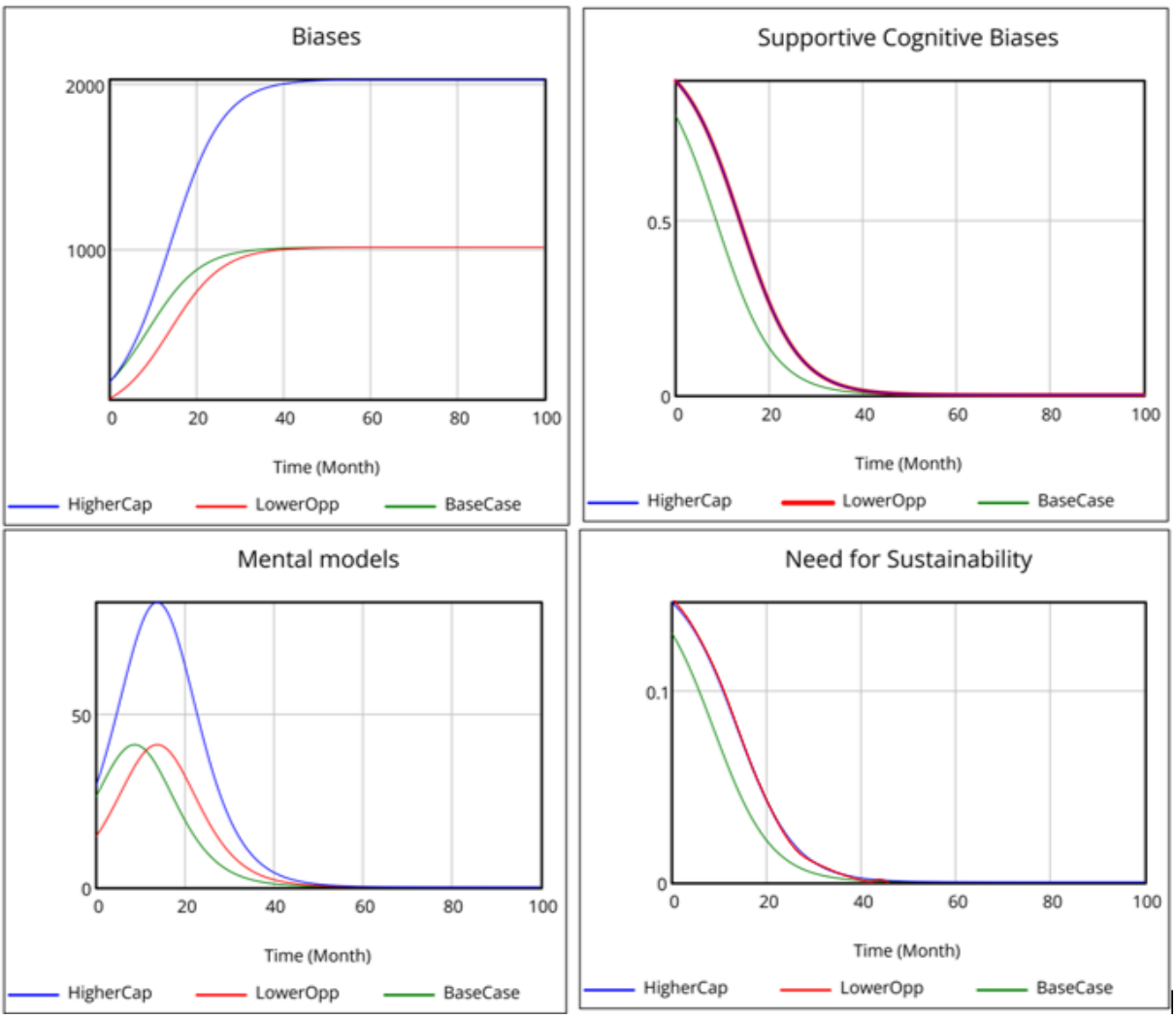

Figure 65. Simulation outputs from empirical data of SFD. (van der Linde et al., 2023:5-18)

Biases (Stock) graph in Figure 66: This graph exhibits a characteristic S-shaped growth pattern, typical of limits to growth models. It reflects exponential growth during the early stages, followed by an inflexion point where the pattern shifts. Notably, the bottom red line illustrates that when opposing biases diminish to zero, society's mental models evolve towards a more sustainable and holistic outlook. Conversely, when the capacity for opposing biases increases, as shown in the blue line, the supportive biases cannot recover the system to the baseline.

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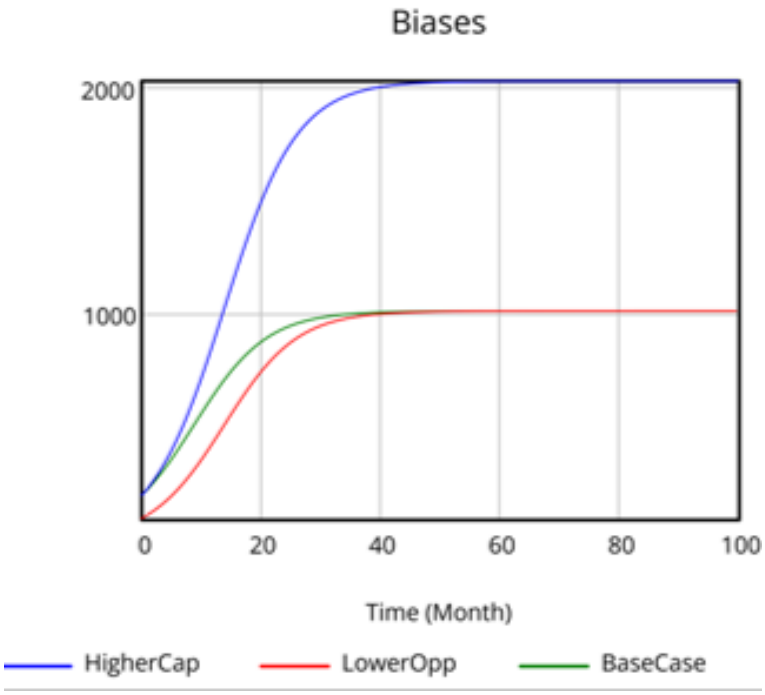

Figure 66. Simulation outputs from empirical data of SFD - Biases

Supportive Cognitive Biases graph in Figure 67: This graph shows that supporting biases peak when the stock of overall biases is at its lowest. This pattern is consistent with the explanation of mental models from the first graph. As overall biases increase, the influence of supporting biases diminishes due to the residual opposing biases. The red and blue lines coincide because the changed variables relate to the opposing biases. This indicates that the availability ratio of supportive biases between 0 and 1 decreases over time as opposing biases increase.

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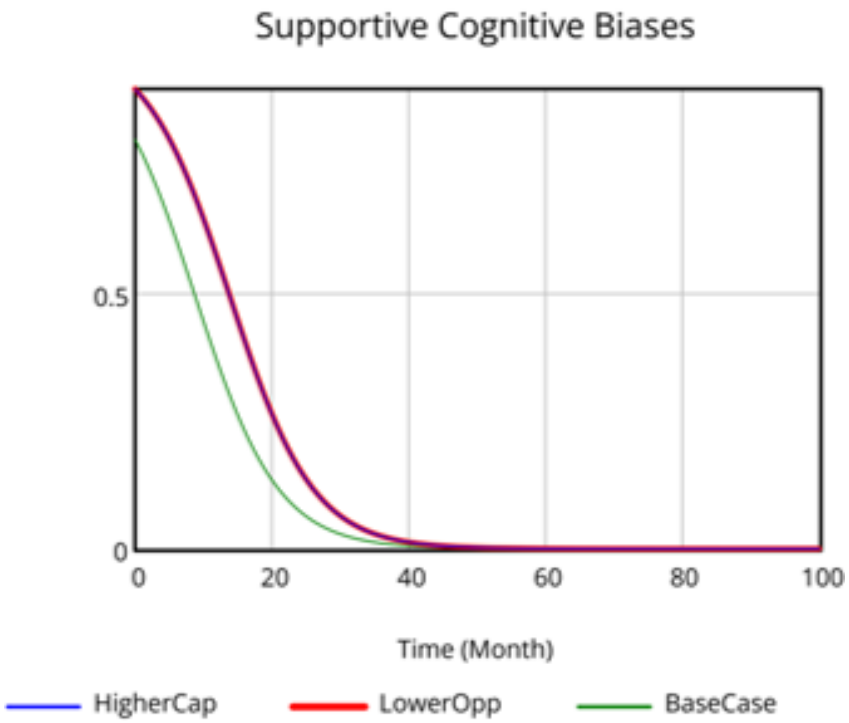

Figure 67. Simulation outputs from empirical data of SFD - Supportive Cognitive Biases

Need for Sustainability graph in Figure 68: Linked to Equation (1), this graph is influenced by biases. A decrease in the plot corresponds to a decline in supporting biases. The system reaches a zero point when opposing biases surpass supporting biases, indicating that further growth becomes unattainable. The higher capacity blue line and lower initial opposing biases red line coincide, showing that the perceived need for sustainability takes longer to decrease over time.

By interpreting the model as a decision-making tool, stakeholders can proactively identify when opposing biases begin to outweigh supporting biases, signalling a risk of losing momentum in sustainable efforts. This can guide interventions such as policy adjustments, awareness campaigns, or systemic reinforcements that sustain the perceived need for sustainability beyond its natural decline. Additionally, the model can highlight critical thresholds where reinforcing positive cognitive biases—such as long-term thinking and systemic awareness—can prolong sustainability efforts and prevent regression. Instead of viewing the zero point as an inevitable collapse, the model offers a strategic framework for ensuring continuous engagement with sustainability, helping to maintain the economic, social, and environmental dimensions of the CE over time.

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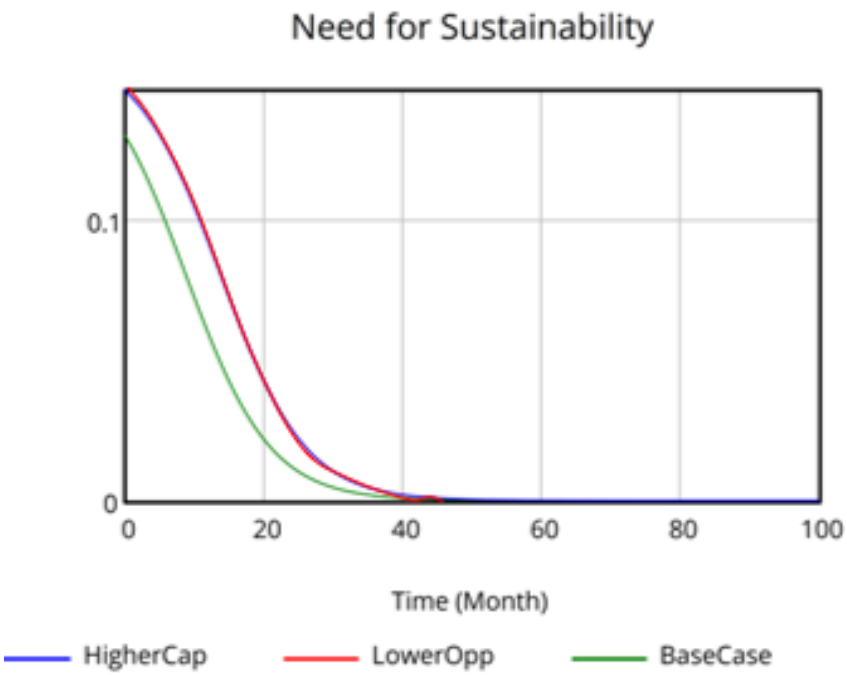

Figure 68. Simulation outputs from empirical data of SFD - Need for Sustainability

Mental Models of society graph in Figure 69: The final graph illustrates the evolution of society's mental models. Lower values (<50) signify simpler mental models, while higher values indicate complexity. The graph adopts a characteristic bell-shaped curve, with exponential growth leading to a peak and a subsequent decline towards zero. This decline suggests that the mental models are no longer primarily influenced by biases after a certain point in time. Instead, they are driven by the system's net flow of perceived needs, a phenomenon aligned with the 'business-as-usual' effect (Meadows et al., 2006:397-399). The green and red line scenarios are closer to each other, indicating that with a low capacity for biases and lower opposing biases, the mental models do not significantly influence sustainability focus. Conversely, when decision-makers have many opposing biases, their mental models over time directly influence sustainability.

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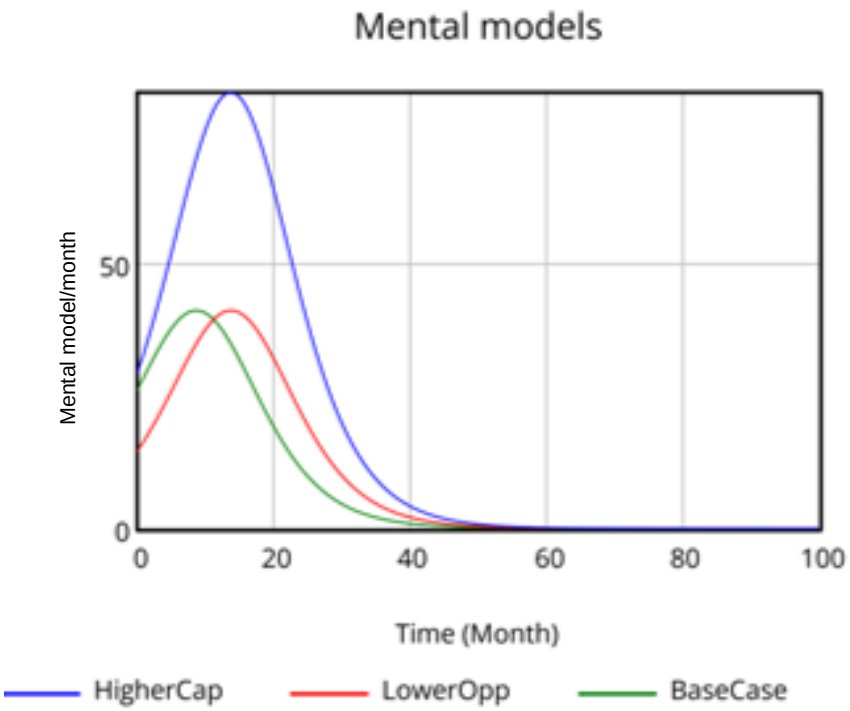

Figure 69. Simulation outputs from empirical data of SFD - Mental Models

In conclusion, the study's results provide crucial insights into the complex dynamics of biases, sustainability perceptions, and societal mental models. These findings have significant implications for decision-makers, policymakers, and researchers alike (Hartley et al., 2020:3-6). The simulations revealed that opposing and supportive biases are pivotal in shaping mental models and the perceived need for sustainability. The presence of supportive biases is essential for maintaining the perceived need for sustainable actions.

Moreover, the diminishing impact of opposing biases leads to more holistic and sustainable mental models, while a surge in opposing biases can hinder efforts to revert to a more sustainable trajectory. These findings underscore the importance of addressing biases in efforts to promote sustainable practices and inform strategic decisions.

The comparison between the auxiliary simulations in Chapter 4.7 of this SFD and the results in this chapter are as follows:

Table 24. Simulation comparison between auxiliary and empirical data in Vensim

Graph title	Auxiliary data simulation result from Chapter 4.7.	Survey (empirical) data simulation result from Chapter 6.4.1
Biases	The graph shows s-shaped growth with exponential growth initially, followed by a plateau when opposing biases reach zero, transforming mental models into sustainable ones. The plateau was reached only after 100 months, and the	The S-shaped growth pattern reflects the limits to growth model, where exponential growth is followed by a shift at the inflexion point. When opposing biases diminish, mental models evolve towards sustainability, but increased opposing

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	peak was much higher at 15000. (Figure 57)	biases prevent recovery. The plateau is reached after 40 months, and the peak is lower at 2000. (Figure 66)
Supportive Cognitive Biases	Supportive biases are highest when the stock of biases is lowest, indicating that supporting and opposing biases counteract each other. The lowest point is reached between 60 and 80 months. (Figure 58)	The supporting biases peak when overall biases are low. However, as opposing biases increase, the influence of supporting biases diminishes, and they cannot restore the system to its baseline. The lowest point is reached after 40 months. (Figure 67)
Mental models	Mental models follow a bell curve, with growth followed by a decline as biases cease to be influenced, showing the 'business-as-usual' effect. Peaks after 40 months. (Figure 60)	The mental model's graph follows a bell curve, with simpler models growing to complexity before declining. This indicates that biases eventually stop influencing mental models, which are instead driven by the perceived need for sustainability. Peaks before 20 months. (Figure 69)
Need for sustainability	The need for sustainability plateaus when opposing biases surpass supporting biases, as shown by the SD model. Plateaus between 70 and 100 months. (Figure 59)	The graph linked to Equation (1) shows that the system reaches a zero point when opposing biases surpass supporting biases, making further growth unattainable. The decline in supporting biases corresponds to a diminished perceived need for sustainability. Plateaus at 40 months. (Figure 68)

The discrepancy in the Biases graphs suggests that empirical data reveals a more rapid evolution of biases, with real-world dynamics settling faster than predicted by the auxiliary model. The earlier decline in the empirical data in the Supportive Cognitive Biases graph may suggest that in real-world scenarios, the interplay between supportive and opposing biases is more volatile and occurs more quickly than in the initial theoretical simulations. The Mental model graphs suggest that societal mental models are quicker to develop and reach complexity but may also decline sooner than anticipated in theoretical models, potentially indicating faster shifts in societal thinking in real-world situations. Lastly, the Need for Sustainability graphs indicate that, in practice, stakeholders may perceive the limits to sustainability much earlier, potentially due to faster-growing opposing biases than anticipated in the auxiliary model.

In summary, while the general patterns between auxiliary simulations and empirical data are consistent, the survey results suggest a faster progression of biases, supportive cognitive influences, mental models, and sustainability needs in real-world scenarios compared to theoretical models. This implies that, in practice, decision-makers may need to act more swiftly to mitigate biases and support sustainable decision-making as the dynamics of change occur more rapidly than expected.

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These insights into the dynamics of biases, sustainability perceptions, and societal mental models seamlessly transition into the MCDA section. By understanding how biases influence decision-making, the MCDA framework can better incorporate these psychological and behavioural factors, enhancing the robustness and effectiveness of sustainability assessments and policy decisions.

6.4.2. MCDA process

As specified in Section 2.5, applying MCDA to this study is crucial for the DSR methodology. The aim is to identify the criteria and weights based on the survey content and then assess each option against these criteria. See Appendix C – Raw data from surveys for detailed survey results.

- Criteria:
  - Impact on mental models: How effectively does the option influence societal mental models towards sustainability?
  - Alignment with sustainability goals: To what extent does the option align with long-term sustainability objectives?
  - Feasibility: How feasible is the option to implement in real-world decision-making contexts?
  - Potential for bias leveraging: How well do the options address leveraging cognitive biases in decision-making?
  - Long-term effectiveness: How likely is the option to maintain its effectiveness in promoting sustainability over the long term?

- Weights: Weights assigned to each criterion are based on the perceived importance of the surveys in promoting sustainable decision-making. See Appendix I – Model Development 7 for information regarding the weights vs grounded frequencies.
  - Impact on mental models: 0.25
  - Alignment with sustainability goals: 0.2
  - Feasibility: 0.15
  - Potential for bias leveraging: 0.25
  - Long-term effectiveness: 0.15

- Options:
  - Implement targeted bias leverages strategies based on survey findings.
  - Develop and implement educational programs to raise awareness about biases in decision-making.
  - Incorporate bias awareness training into policymaker and stakeholder workshops.
  - Conduct longitudinal studies to monitor the evolution of biases and mental models over time.

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- Establish interdisciplinary research collaborations to develop more sophisticated models for bias analysis.

- Assessment: For each option, the researcher rated its effectiveness on a scale of 1 to 5 for each criterion, where:
  - 1 - Very Low
  - 2 - Low
  - 3 - Moderate
  - 4 - High
  - 5 - Very High

- Outcome:
  - Implement targeted bias leverage strategies:
    - Impact on Mental Models: 4
    - Alignment with Sustainability Goals: 3
    - Feasibility: 4
    - Potential for Bias leveraging: 5
    - Long-Term Effectiveness: 4
    - Total Score: (4 * 0.25) + (3 * 0.2) + (4 * 0.15) + (5 * 0.25) + (4 * 0.15) = 4.05

  - Develop and implement educational programs:
    - Impact on Mental Models: 3
    - Alignment with Sustainability Goals: 4
    - Feasibility: 3
    - Potential for Bias leveraging: 4
    - Long-Term Effectiveness: 3
    - Total Score: (3 * 0.25) + (4 * 0.2) + (3 * 0.15) + (4 * 0.25) + (3 * 0.15) = 3.45

  - Incorporate bias awareness training:
    - Impact on Mental Models: 4
    - Alignment with Sustainability Goals: 3
    - Feasibility: 3
    - Potential for Bias leveraging: 4
    - Long-Term Effectiveness: 3
    - Total Score: (4 * 0.25) + (3 * 0.2) + (3 * 0.15) + (4 * 0.25) + (3 * 0.15) = 3.7

  - Conduct longitudinal studies:
    - Impact on Mental Models: 3
    - Alignment with Sustainability Goals: 3
    - Feasibility: 4
    - Potential for Bias leveraging: 3
    - Long-Term Effectiveness: 5

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- Total Score: (3 * 0.25) + (3 * 0.2) + (4 * 0.15) + (3 * 0.25) + (5 * 0.15) = 3.65

- Establish interdisciplinary research collaborations:
  - Impact on Mental Models: 5
  - Alignment with Sustainability Goals: 4
  - Feasibility: 2
  - Potential for Bias leveraging: 3
  - Long-Term Effectiveness: 4
  - Total Score: (5 * 0.25) + (4 * 0.2) + (2 * 0.15) + (3 * 0.25) + (4 * 0.15) = 3.75

Based on the MCDA assessment, the option "Implement targeted bias leverage strategies" has the highest total score of 4.05, indicating that it is the most effective option for promoting sustainable decision-making within the CE. However, it is essential to consider the context and specific objectives of the decision-making process when selecting the most suitable option. To evaluate different leverage points, the following CLD was constructed: Artificial Intelligence (AI) and Technology Management (TM). Linking the MCDA to the dynamic CLD presented in the following section, the research explores the relationships between sustainable TM initiatives, CE model adoption, and AI integration. The MCDA framework was instrumental in evaluating multiple criteria and stakeholders' perspectives, enriching our understanding of the feedback loops and causal connections revealed by the CLD. This holistic approach supports strategic planning and decision-making in technology-centric ecosystems by highlighting how biases and societal perceptions influence these systems.

Through the MCDA, the research better assessed the impacts of adopting CE models. Now, the study integrates AI within sustainable TM, providing actionable intelligence to sustainably guide the transition from theory to practice in managing technology.

6.4.3. VISIS, SIMILAR and AHP Process

This study aims to develop a systematic framework for modelling, analysing, and managing decision-making in the CE, focusing on the influence of cognitive biases on sustainable decision-making processes. The study seeks to establish a linkage between cognitive biases and unsustainable activities and to leverage these influences to enhance sustainability.

To achieve this aim, the study integrates the VISIS framework, SIMILAR framework, EMF CE framework, and AHP into a cohesive approach. Here's an example of how this linked framework is applied to the study's aim and results:

- VISIS framework in the study, as discussed in 2.2.1 and Figure 9:
  - Vision: The study envisions a CE where decision-making processes are free from biases, leading to sustainable outcomes across industries and stakeholder

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groups.
  - Indicators: Key performance indicators (KPIs) are established to measure the presence and impact of cognitive biases in decision-making, such as the frequency of biased decisions and their sustainability impacts.
  - Systems: The study maps the decision-making systems within the CE, identifying how biases manifest and influence outcomes at different stages and among various stakeholders.
  - Innovation: Innovative strategies, such as decision-support tools and training programs, are proposed to mitigate cognitive biases.
  - Strategy: A comprehensive approach is developed to implement these innovations within the CE framework, ensuring continuous improvement and adaptation.

- SIMILAR framework in the study as discussed in 2.3.3 and Figure 15:
  - State: The problem of cognitive biases in decision-making is clearly stated, highlighting its detrimental effects on sustainability within the CE.
  - Investigate: A thorough investigation is conducted to understand the extent and nature of cognitive biases among stakeholders.
  - Model: Conceptual models are developed to illustrate how biases influence decision-making processes within the CE.
  - Integrate: The models are integrated into existing CE frameworks to test their validity and effectiveness.
  - Launch: Pilot programs and interventions are launched to address identified biases.
  - Assess: The impact of these interventions is assessed through empirical studies, comparing pre- and post-intervention decision-making outcomes.
  - Re-evaluate: Continuous re-evaluation is conducted to refine the models and strategies, ensuring they remain practical and relevant.
- EMF CE framework in the study, as discussed in 2.4.1 and Figure 16:
  - Design out waste: The study identifies decision-making processes that lead to waste and proposes methods to eliminate these through better decision-making.
  - Keep products and materials in use: By reducing cognitive biases, decisions can be made by prioritising the longevity and reuse of materials.
  - Regenerate natural systems: Sustainable decision-making ensures that natural systems are not depleted, aligning with the CE principle of regeneration.

- Analytic Hierarchy Process in the study, as discussed in 2.5.1 and Figure 23
  - Prioritisation: AHP prioritises the cognitive biases that significantly impact decision-making within the CE. This helps focus efforts on the most critical areas.
  - Evaluation: Different strategies to mitigate these biases are evaluated using AHP, ensuring that the most effective methods are chosen.
  - Decision-making: AHP supports stakeholders in making informed, objective

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decisions by providing a structured approach to evaluating options and their sustainability impacts.

By applying the VISIS framework, the study identifies critical cognitive biases affecting decision-making in the CE and establishes indicators to measure their impact.

Using the SIMILAR framework, the study develops and validates conceptual models that illustrate the influence of biases on decision-making processes, integrating these models into existing CE frameworks.

Leveraging the EMF CE framework, the study proposes practical interventions, such as decision-support tools and training programs, to mitigate cognitive biases and promote sustainability.

With AHP, the study prioritises critical biases and evaluates interventions, leading to more informed and objective decision-making processes that support the CE.

By integrating the VISIS, SIMILAR, EMF CE framework, and AHP, the study creates a comprehensive approach to understanding and mitigating cognitive biases in decision-making within the CE. This linked framework addresses the research objectives and provides practical tools and strategies to enhance sustainability outcomes, making it a valuable contribution to theory and practice. The summaries above for each method clearly states the value of the integration to the rest of the research.

6.4.4. Causal Loop Diagram of Current CE Stakeholders and Their Decision-Making Power in the Industry

This section investigates the complex dynamics and relationships within technology-centric ecosystems. Using a dynamic CLD and ST, our research seeks to elucidate how AI positively impacts CE models through sustainable Technology Management initiatives. It serves as more than just an academic endeavour; it provides a roadmap for decision-makers navigating the intersection of technology and sustainability in today's interconnected world. The research employed a qualitative method to grasp the subject matter, ensuring a holistic approach comprehensively. Through focus groups and literature reviews, several prior CLDs from Sections 3 and 4 underwent evaluation and modification, culminating in constructing the diagram depicted in Figure 70. See section 3.3.6 for a detailed model development discussion.

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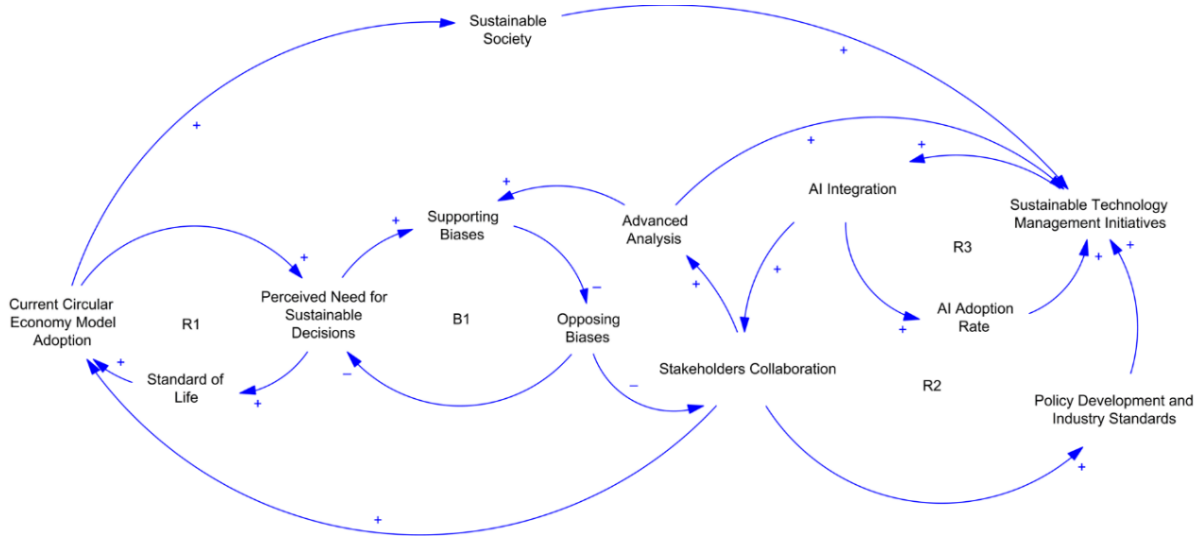

Figure 70. Leverage points from thematic cause and effects. (van der Linde et al., 2024:1-10)

Circular Economy Model Adoption positively influences a sustainable society by reducing resource depletion and environmental impact. Adopting CE models increases the perception of the need for sustainable decisions, driven by heightened awareness and visibility of sustainable practices. Higher living standards drive the adoption of CE models as the demand for sustainable products and services increases. This is further reinforced by the availability of improved and eco-friendly options, enhancing the standard of living.

Individuals with a high perceived need for sustainable decisions often develop biases that support CE practices. However, these supporting biases may face opposition from those with opposing biases, creating tensions and challenges in the adoption process. Opposing biases can downplay the perceived need for sustainable decisions, creating a negative loop. These biases also negatively impact stakeholder collaboration due to conflicting interests, ideological differences, external influences, and cultural norms.

Active engagement among stakeholders, including government bodies, industry players, and civil society, positively influences the adoption of CE models. Effective collaboration fosters policy development and industry standards that support sustainable technology management initiatives. A sustainable society, which values ecological responsibility, social equity, and economic viability, drives the development and implementation of these initiatives.

Sustainable Technology Management Initiatives (STMI) contribute positively to AI integration. Emphasising responsible and sustainable practices, STMI leverages AI to enhance technology management efficiency, innovation, and agility. With its advanced capabilities, AI integration facilitates data analysis, predictive modelling, and decision-making, enhancing stakeholder collaboration and optimising resource management.

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Stakeholder collaboration generates diverse perspectives and data, fueling advanced analytical processes. This collective input leads to comprehensive and nuanced analyses, enabling organisations to derive deeper insights and make informed decisions. Sophisticated analytical methods within sustainable technology management initiatives refine and inform strategic directions, contributing to their effectiveness and success.

However, advanced analysis can also reinforce certain biases in sustainability, especially if historical data or models contain pre-existing biases. Ethical considerations are crucial to ensure that insights derived from advanced analysis align with genuine sustainability goals and principles.

Supportive policies and industry standards create a conducive environment for the success of sustainable technology management initiatives, further promoting CE practices. Overall, AI positively impacts CE models through sustainable TM initiatives. Integrating similar variables and loops from Figure 50 into a comprehensive CLD showcases the detailed influences of biases, TM, and AI.

6.5. Conclusion

In conclusion, the Results chapter is a pivotal component of this thesis, unveiling the empirical evidence and insights into bias identification and decision-making influences within sustainability and the CE. The comprehensive analysis of data and the juxtaposition of quantitative and qualitative findings aim to contribute to the broader body of knowledge in this research domain and inform actionable recommendations for promoting sustainable practices. The results presented in this section mark a significant step forward in advancing our understanding of sustainable decision-making processes and serve as a valuable resource for stakeholders, policymakers, and researchers.

The empirical testing and analysis of results are integral parts of the DSR process, with each finding representing a research outcome that informs the iterative refinement of the model.
This section focuses on data analysis, applying various methods to validate the findings. It links to the validation and verification processes discussed in Chapter 7. In the following chapter, a Monte Carlo analysis is used to validate and explore the survey results, and it is further used in an SFD simulation to validate the diagrams used in this chapter.

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7. Validation and Verification

In this chapter, the data validation and verification processes are conducted. The final model is compared to the conceptual model developed in Chapter 4.

In this chapter, the research shows how to validate and verify the proposed framework, demonstrating that integrating cognitive biases into SE models results in more accurate and actionable insights. As software user interfaces must be tested with real users to ensure it meets their needs, the validation process confirms that considering both technical and human elements enhances sustainable decision-making for CE stakeholders. This section fits into the DSR framework of the thesis, as shown in Figure 71.

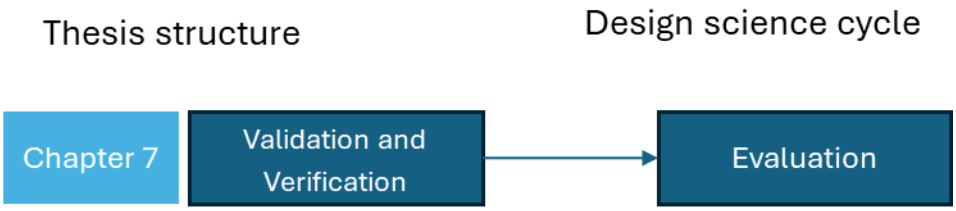

Figure 71. Design Science Research Framework - Chapter 7

7.1. Introduction

This section introduces the methodologies and processes used to validate and verify the research findings related to cognitive biases in adopting the CE. It outlines the data validation and model verification procedures applied to ensure the applicability of the results.

7.2. Data Validation

Data validation involved data extraction and coding from the authors' conference papers. The extracted data included key findings, methodologies, and insights into cognitive biases affecting CE adoption. The coding process was conducted deductively, guided by existing literature, and inductively, allowing new themes to emerge from the data. This dual approach ensured a comprehensive understanding of recurring themes and patterns related to cognitive biases and CE adoption. This is part of the evaluation phase, as seen in Figure 72.

The decision to extract and code data from the conference papers as part of the evaluation phase was driven by several key factors. First, these papers contain valuable insights into the methodologies, findings, and discussions that reflect the research on cognitive biases affecting CE adoption. Since conference papers often present novel ideas, preliminary results, and early-stage innovations, they serve as rich data sources that capture the latest trends and emerging challenges within the

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field. Analysing these papers ensures that the evaluation phase incorporates contemporary perspectives and developments relevant to the research topic. These papers also used the data gathered in Section 6.

Second, using data from the conference papers provides continuity and consistency with the broader scope of the thesis. The findings and methodologies presented in these papers are directly linked to the research objectives, ensuring alignment with the thesis's core focus on cognitive biases and decision-making within the CE framework. Integrating these papers into the evaluation process makes it possible to systematically assess recurring themes, validate emerging patterns, and ensure that the thesis's conclusions are built on a robust foundation of empirical evidence that spans multiple stages of the research. This strengthens the validity and depth of the analysis, making it comprehensive and contextually relevant to sustainable decision-making.

The thematic analysis synthesised the coded data into broader themes, enhancing understanding of the relationship between cognitive biases and CE adoption. Software tools like Atlas.ti and Microsoft Excel were used to facilitate this analysis, ensuring the efficiency and effectiveness of the research process. See Appendices 6, 7, 8 and 9.

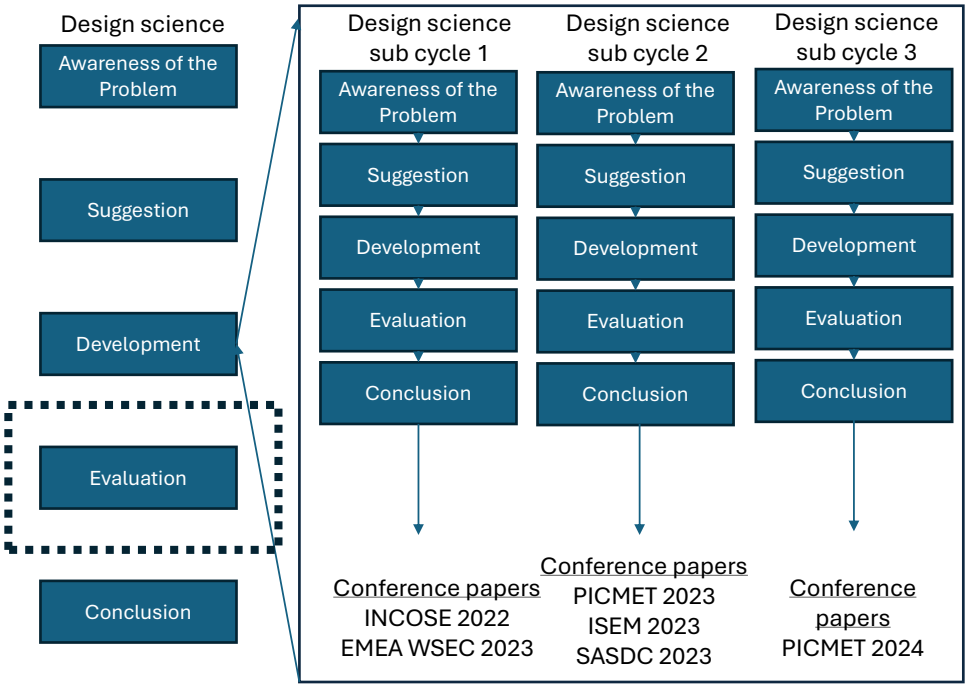

Figure 72. The evaluation phase of the overall DSR methodology

The evaluation phase in the DSR method, shown in Figure 72, ensures the developed artefact's accuracy, reliability, and robustness are paramount. This phase is crucial for confirming that the artefact meets its design objectives and performs effectively under varying conditions. To achieve this, methods are employed to test and validate the artefact's performance and outcomes.

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Monte Carlo analysis emerges as a powerful tool in this context, offering a sophisticated approach to data validation (Banack et al., 2021:106-117; Constantin et al., 2023:1-22). By leveraging Monte Carlo simulations, researchers can explore a wide range of scenarios and assess the probabilistic behaviour of the artefact (Jamroz and Williams, 2020:1-8). This technique generates numerous random samples based on defined statistical distributions to model various possible outcomes and uncertainties associated with the artefact (Herrera et al., 2022:1-6).

The application of Monte Carlo analysis in the V&V phase provides several key advantages. First, it quantifies uncertainty by presenting a range of potential outcomes and their probabilities rather than relying on single-point estimates. This comprehensive view of uncertainty helps understand the variability in the artefact's performance and reliability across different conditions.

Second, Monte Carlo simulations enable the exploration of complex and non-linear interactions that traditional validation methods might not capture. By simulating many scenarios, researchers can evaluate how different factors and assumptions impact the artefact's performance, providing deeper insights into its robustness and effectiveness.

Finally, Monte Carlo analysis supports evaluation by allowing extensive testing and validation of the artefact under diverse conditions. The simulation results can highlight potential weaknesses and areas for improvement and ensure that the artefact meets the design specifications and requirements.

7.2.1. Introduction to Monte Carlo Analysis and Distributions

Monte Carlo analysis is a statistical method that uses repeated random sampling to obtain a distribution of an unknown probabilistic entity (Kroese et al., 2014:386-392). This technique is highly effective for understanding the impact of risk and uncertainty in prediction and forecasting models. By running many simulations, Monte Carlo analysis helps identify possible outcomes and the likelihood of different scenarios occurring (Raychaudhuri, 2008:91-100; Pensado, 2024:87-148).

In this section, it is important to note that the Monte Carlo values and their corresponding fit were manually calculated, rather than being derived through Vensim's Monte Carlo sensitivity analysis option. This manual approach involved using the collected data and performing statistical calculations outside of the Vensim environment to assess the distribution and fit of the variables. The decision to calculate these values manually was made to ensure a more controlled and precise analysis, allowing for a deeper understanding of the data without relying on the automated simulation processes within the software. While Vensim offers built-in functionality for conducting Monte Carlo simulations, in this instance, the calculations were deliberately

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performed manually to maintain greater oversight and accuracy throughout the analysis process.

The Weibull distribution, a versatile and widely used probability distribution, is beneficial for analysing data, modelling failure times, and assessing product reliability. It is defined by two parameters: the shape parameter (β), which dictates the distribution's shape, and the scale parameter (η), which stretches or compresses the distribution along the horizontal axis (Bhattacharya and Bhattacharjee, 2010:234-241). The flexibility of the Weibull distribution allows it to model various types of data, making it an essential tool in reliability engineering and failure analysis (Teimouri et al., 2013:93-109). The flexibility of the Weibull distribution is highly relevant to this research, particularly in modelling the complex patterns of decision-making behaviour and cognitive biases within the CE framework. Just as the Weibull distribution is used in reliability engineering and failure analysis to model different types of failure rates, it can be applied in this research to understand and predict the variability in how individuals or organisations adopt sustainable practices, influenced by cognitive biases.

In the context of this research, the Weibull distribution's ability to model various types of data allows for a more nuanced representation of decision-making processes over time. Cognitive biases may lead to different "failure" rates in the adoption of sustainability measures—ranging from immediate adoption to delayed or failed implementation. By applying the Weibull distribution, these varying patterns are captured, providing insights into how biases affect long-term sustainability outcomes and decision reliability, thus enhancing the overall analysis of cognitive biases in CE adoption.

Accurately fitting a distribution to survey data is crucial for deriving meaningful insights in statistical analysis. While the Weibull distribution is commonly used for its flexibility in modelling various data types, its fit may not always be ideal for specific datasets. This study explores the use of the Normal distribution as an alternative, given its properties and widespread application in natural and social sciences. The initial attempts with the Weibull distribution yielded unsatisfactory results for some questions, prompting a transition to the Normal distribution to better model the survey data. This thesis presents the methods and results of fitting a normal distribution to the survey data, demonstrating its suitability over the Weibull distribution.

In the initial stages of the data analysis, a Weibull distribution was chosen to fit the survey data due to its versatility in modelling various types of data distributions. The Weibull distribution is beneficial in scenarios involving skewed data or data with non-constant failure rates, as it can accommodate a range of distribution shapes through its shape parameter. This makes it a robust choice for preliminary analysis, mainly

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when the data exhibits characteristics that are not well-represented by more common distributions.

The observed fit of the Weibull model drove the decision to transition from the Weibull distribution to a normal distribution, as will be seen in the following section. While the Weibull distribution effectively models data with complex shapes and skewness, its fit might reveal that the data tends towards a more symmetric distribution. If residual analysis indicates that the data is closer to a normal distribution—characterised by its bell-shaped curve and symmetry—it becomes appropriate to explore the normal distribution for further analysis. The normal distribution is widely utilised due to its well-established statistical properties and applicability to data exhibiting a symmetric pattern.

Simulations were conducted to assess the fit of each distribution. Initially, 1000 simulations were run for the Weibull distribution. Given the distribution's flexibility and ability to model a range of shapes with fewer simulations, this number was deemed sufficient to obtain a reliable fit estimate. Subsequently, a more significant number of 5000 simulations was employed for the normal distribution. This increased number of simulations was necessary to achieve higher precision and confidence in estimating the fit, particularly for a distribution with fewer parameters and more straightforward shape characteristics. Running more simulations for the normal distribution allows for a more accurate assessment of its fit to the data and ensures robust statistical properties are captured.

The transition from Weibull to normal distribution reflects a shift from a flexible model capable of handling diverse data shapes to a more specific model suited for data exhibiting symmetry. Using varying simulation numbers aligns with each distribution's computational demands and precision requirements.

7.2.2. Application of Monte Carlo Analysis to Survey Quantitative Results

In this study, Monte Carlo analysis is applied to the survey quantitative results to assess the variability and reliability of responses. See Section 6.3 for the data gathering discussion and Appendices 2 and 3 for the survey data details. By simulating numerous scenarios based on the collected survey data, the research can estimate the probability distribution of outcomes and provide a comprehensive understanding of the underlying patterns. The Python coding for the following Monte Carlo analyses can be found in Appendix D – Phyton coding. See Table 30 for the comparative results between the surveys and the Monte Carlo simulations.

The difference in numbering between the original survey questions and the numbering used in the Weibull analysis arises from the focus on specific quantitative survey questions that are relevant to the analysis, as seen in Table 25. In the survey design,

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the questions are numbered sequentially (e.g., 2, 7, 8, etc.) based on their overall placement within the survey instrument, which includes both qualitative and quantitative questions. However, for the purposes of the Weibull analysis, only the quantitative data points are being used, necessitating a re-numbering system.

By re-numbering the relevant quantitative survey questions (e.g., 2, 7, 8) as 1, 2, 3 in the analysis, the focus remains solely on the data that can be modelled and analysed using the Weibull distribution. This simplification ensures clarity in the analysis, helping to streamline the process and avoid confusion. It also emphasises the quantitative aspect of the research, enabling a more straightforward and organised interpretation of the data, particularly when applying statistical models like the Weibull distribution to assess patterns, reliability, or trends in decision-making behaviour.

The steps to apply Monte Carlo analysis to survey data include:

- Data Collection: Shown in Section 6.3:

Table 25 presents a detailed alignment of the survey questions with the corresponding Monte Carlo simulations. Each quantitative answer from the surveys is linked to its relevant simulation, allowing for a more comprehensive analysis of how cognitive biases influence decision-making in the CE. By mapping the questions to the simulation data, this table serves as a reference point for tracking how survey responses are modelled and analysed in subsequent sections. The insights gained from this mapping will be essential for understanding the broader impacts of biases on stakeholder behaviour.

Table 25. Survey questions vs Monte Carlo numbering (only quantitative answers analysed)

Survey question #	Monte Carlo question #	Question	Possible answers to the survey	Possible Answers : Monte Carlo
2	1	Do you believe sustainability should be focused on?	"Yes", "No"	0, 1
7	2	Are you willing to change your habits to be more sustainable?	"Yes", "No"	0, 1
8	3	Do you think that the benefits of economic growth and development should outweigh the costs to the environment?	"Yes", "No"	0, 1
9	4	Do you believe that governments should take a more active role in promoting sustainability, even if it means limiting individual freedom of choice or imposing strict regulations?	"Yes", "No"	0, 1

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11.1	5	Please select the options below that best represent your answer for each statement >> How informed are you about sustainability issues?	"Very poor", "Poor", "Average", "Good", "Excellent"	0, 1, 2, 3, 4
11.2	6	Please select the options below that best represent your answer for each statement >> How confident are you in your ability to make environmentally friendly choices in your daily life?	"Very poor", "Poor", "Average", "Good", "Excellent"	0, 1, 2, 3, 4
12.1	7	Please select the options below that best represent your answer for each statement >> Would you spend more money to buy repaired, re-used or recycled products than new ones?	"Very unlikely", "Somewhat unlikely", "Neither likely nor unlikely", "Somewhat likely", "Very likely"	0, 1, 2, 3, 4
12.2	8	Please select the options below that best represent your answer for each statement >> How willing are you to make changes to your lifestyle or consumption habits in order to support sustainability and protect the environment?	"Very unlikely", "Somewhat unlikely", "Neither likely nor unlikely", "Somewhat likely", "Very likely"	0, 1, 2, 3, 4
12.3	9	Please select the options below that best represent your answer for each statement >> How much do you believe that cognitive biases can impact the success or failure of circular economy initiatives?	"Very unlikely", "Somewhat unlikely", "Neither likely nor unlikely", "Somewhat likely", "Very likely"	0, 1, 2, 3, 4
13	10	Please select the options below that best represent your answer for each statement >> How often do you make an effort to reduce your carbon footprint or limit your use of single-use plastics?	"Never", "Rarely", "Sometimes", "Often", "Always"	0, 1, 2, 3, 4
14.1	11	Please select the options below that best represent your answer for each statement >> Do you agree with the following view: Is it imperative to reduce the use of fossil fuels in our daily lives, by increasing the demand for sustainable products?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.2	12	Please select the options below that best represent your answer for each statement >> Do you agree that it is important that society follows environmentally friendly practices?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.3	13	Please select the options below that best represent your answer for each statement >> Do you agree with the following view: There is no proper manner to change the awareness of the public for the establishment of a more sustainable reality?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4

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14.4	14	Please select the options below that best represent your answer for each statement >> Do you think it is important for individuals to take action to reduce their impact on the environment?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.5	15	Please select the options below that best represent your answer for each statement >> To what extent do you believe that environmental problems can be solved through technology and innovation?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.6	16	Please select the options below that best represent your answer for each statement >> To what extent do you believe that businesses should prioritise sustainability in their decision-making?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.7	17	Please select the options below that best represent your answer for each statement >> To what extent do you think that climate change is caused by human activity?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.8	18	Please select the options below that best represent your answer for each statement >> To what extent do you believe that cognitive biases influence decision-making in the adoption of circular economy principles and practices?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4
14.9	19	Please select the options below that best represent your answer for each statement >> To what extent do you think that cognitive biases play a role in the resistance to change and adoption of circular economy practices?	"Strongly Disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree"	0, 1, 2, 3, 4

- Model Selection: Choosing the appropriate statistical model to fit the survey data, such as the Weibull distribution over 79 valid responses.

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Table 26 summarises the statistical analysis of the survey results, providing a snapshot of key metrics such as means, standard deviations, and distributions of the responses. This analysis is critical for identifying patterns in stakeholder decision-making and understanding the prevalence of cognitive biases within the surveyed population. The data shown in this table form the basis for further simulation and validation, enabling the identification of leverage points for promoting sustainable decision-making in the CE.

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Table 26. Survey results from statistical analysis

Survey results (actual)								
Possible answers	**Question #**	**Average**	**Median**	**Mode**	**Stand Dev**	**Confidence Interval (95%)**	**Lower Bounds of the Confidence Interval**	**Upper Bounds of the Confidence Interval**
Yes=1, No=0	1	0,987	1	1	0,111	0,0246	0,962	1,011
	2	0,987	1	1	0,111	0,0246	0,962	1,011
	3	0,189	0	0	0,392	0,086	0,103	0,276
	4	0,645	1	1	0,478	0,105	0,540	0,751
Very poor=0 Poor=1 Average=2 Good=3 Excellent=4	5	2,392	2	2	0,718	0,158	2,233	2,550
	6	2,392	2	3	0,833	0,183	2,208	2,576
Very unlikely =0, Somewhat unlikely=1, Neither likely nor unlikely=2, Somewhat likely=3 , Very likely=4	7	1,759	1	3	1,314	0,289	1,469	2,0492
	8	3,151	3	3	0,764	0,168	2,983	3,3204
	9	3,139	3	4	0,924	0,203	2,935	3,343024964
Never=0, Rarely=1,Sometimes=2, Often=3, Always=4	10	2,253	2	3	0,934	0,205	2,047	2,459
Strongly Disagree=0, Disagree=1, Neither agree nor disagree=2, Agree=3, Strongly Agree=4	11	2,974	3	3	0,940	0,207	2,767	3,182
	12	3,329	3	3	0,806	0,177	3,151	3,507
	13	1,645	1	1	1,201	0,264	1,380	1,910
	14	3,316	3	4	0,772	0,170	3,146	3,486
	15	3,329	3	3	0,758	0,167	3,161	3,496
	16	3,227	3	3	0,856	0,188	3,0390	3,416
	17	3,063	3	4	0,997	0,220	2,843	3,283
	18	3,063	3	3	0,816	0,180	2,883	3,243
	19	3,164	3	3	0,833	0,183	2,980	3,348

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Table 27 extends the statistical analysis by diving deeper into the specific relationships between cognitive biases and sustainability outcomes. It offers a comparative discussion of the biases' influence across different CE phases. By highlighting how biases disproportionately affect certain stages, this table provides valuable insights for stakeholders seeking to mitigate unsustainable behaviours.

Table 27. Survey result- Statistical analysis discussion

Question #	Survey result discussion
1	The high average, median, and mode of 1 indicate a strong tendency towards "Yes" responses. The slight standard deviation and narrow confidence intervals suggest a high level of agreement among respondents.
2	
3	The low average and mode of 0 indicate a strong tendency towards "No" responses. The higher standard deviation shows more response variability, with a broader confidence interval.
4	The average is closer to 1, and mode 1 suggests a majority "Yes" response, but the higher standard deviation and confidence interval indicate more response variability.
5	The averages near 2.4 suggest most respondents rated their knowledge or confidence as "Average" to "Good." The standard deviations indicate moderate variability.
6	
7	Responses vary, with some questions showing higher likelihoods (averages around 3) and others indicating more uncertainty (lower averages). The standard deviations reflect significant variability.
8	
9	
10	The average and median suggest responses centred around "Sometimes" to "Often," with the mode indicating a tendency towards "Often."
11	The average close to 3 indicates a general agreement with the statement, and mode 3 reinforces this trend. The standard deviation shows moderate variability.
12	The high average indicates strong agreement with the statement. The mode of 3, combined with a lower standard deviation, suggests consistent responses among participants.
13	The low average and median indicate a tendency towards disagreement. The mode of 1 reinforces this, but the high standard deviation suggests significant variability in responses.
14	The average and mode suggest strong agreement with the statement, with the mode of 4 indicating many respondents strongly agree. The standard deviation shows moderate variability.
15	Similar to question 14, the high average indicates strong agreement. The mode of 3 and low standard deviation suggest consistent responses.
16	The average and mode of 3 indicate agreement. The standard deviation reflects moderate variability among responses.
17	The average and median of 3 suggest general agreement. The mode of 4 indicates a significant number of respondents strongly agree, but the high standard deviation shows variability.
18	Similar to question 17, the average and median of 3 indicate agreement. The three and moderate standard deviations show consistent responses with some variability.
19	The average above 3 suggests strong agreement. The median and mode of 3 show a consistent agreement pattern among respondents, with moderate variability as indicated by the standard deviation.

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- Parameter Estimation: Estimating the selected model's parameters using the survey data.

The Weibull distribution was chosen first for this analysis due to its adaptability and ability to accurately model different types of data distributions. It is particularly effective in representing life data and failure times, which aligns with the survey's aim to assess respondents' attitudes and behaviours regarding sustainability and cognitive biases.

The Weibull distribution is known for its flexibility, as it can model a variety of data types, including those with increasing, constant, or decreasing failure rates. This versatility makes it suitable for a wide range of applications, from engineering to behavioural studies. Another advantage is the parameter interpretability: the shape parameter (β) and the scale parameter (η) offer intuitive insights into the data's characteristics, such as the rate of change and variability over time. Additionally, the Weibull distribution often provides a strong empirical fit, particularly for life data and reliability studies. This makes it a preferred choice for analysing survey responses related to behavioural and cognitive factors, where accurate modelling of patterns and variability is essential.

Table 28 presents the parameters of the two-parameter Weibull distribution fitted to the survey data. The Weibull distribution is utilised to model the probability of certain decision outcomes occurring under the influence of cognitive biases. The table highlights how this distribution helps simulate the variability of stakeholder responses, which is crucial for understanding the uncertainty in decision-making processes. These parameters are further used in simulations to forecast and manage biased decisions in the CE.

Table 28. Two-parameter Weibull distribution

Monte Carlo question #	Eta (shape)	Beta (scale)
1	1.0	1.0
2	1.0	1.0
3	0.05	1.039e-24
4	3919459174.421	0.99
5	3.67	2.65
6	3.21	2.67
7	2.21	2.39
8	1.0	1.05
9	4.61	3.48
10	3.41	2.63
11	4.47	3.34

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12	1.0	1.05
13	1.97	2.11
14	1.0	1.05
15	1.0	1.05
16	1.0	1.05
17	4.42	3.44
18	1.0	1.05
19	1.0	1.05

The Weibull distribution offers significant versatility, allowing it to model different data types, including datasets with varying failure rates. This flexibility makes it particularly useful for applications where the nature of the failure or decision processes is not consistent across different variables. Additionally, the intuitive parameters of the Weibull distribution, specifically the shape and scale parameters, provide meaningful interpretations of the data. These parameters offer insights into the underlying patterns of decision-making or failure processes, making the distribution easy to understand and apply in real-world contexts. Furthermore, the Weibull distribution is known for its good empirical fit, often aligning well with observed data, which enhances its reliability and provides a more insightful analysis. This combination of versatility, interpretability, and empirical robustness makes it a valuable tool for analysing decision-making processes influenced by cognitive biases (Constantin et al., 2023; Luengo et al., 2020:1-62).

Despite its versatility, the Weibull distribution has several limitations. One key limitation is the complexity of parameter estimation, as accurately estimating the shape and scale parameters can be particularly challenging when working with small or censored datasets. This complexity can hinder the application of the Weibull distribution in scenarios where data is limited or incomplete. Additionally, the Weibull distribution exhibits assumption sensitivity, meaning its fit can be highly sensitive to the assumptions made about the underlying data distribution. If incorrect assumptions are made, this can lead to misleading or inaccurate results. Finally, the data requirements for the Weibull distribution are significant, as sufficient and appropriate data is required to estimate parameters effectively and fit the distribution accurately. Without an adequate dataset, the reliability and usefulness of the Weibull model may be compromised (Brown et al., 2008:14-19; Rugen and Callahan, 1996:671-680).

While versatile and widely used for modelling life data and reliability analysis, the Weibull distribution may not be the most accurate for Yes/No questions. Yes/No questions are dichotomous, meaning they have only two possible outcomes. The Weibull distribution, on the other hand, is continuous and is better suited for modelling data with a wide range of potential outcomes (Tian et al., 2021:1-6). When applied to

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Yes/No questions, the Weibull distribution can lead to overfitting or underfitting, as it tries to fit a continuous distribution to binary data (Dash et al., 2023:1132-1149).

This mismatch can result in inaccurate parameter estimation and misleading interpretations of the data. Additionally, the lack of variation in Yes/No responses does not provide enough information for the Weibull distribution to capture meaningful trends or patterns, further limiting its applicability.

In contrast, the Weibull distribution is more accurate and effective for questions with five or more options. These questions generate a broader range of responses, providing a richer dataset for the Weibull distribution to model. The Weibull distribution's shape (β) and scale (η) parameters can capture the nuances and variability in the responses, offering a detailed and accurate representation of the data (Vila and Niyazi Çankaya, 2022:3044-3062; Shama et al., 2023:1-16).

For example, in a survey where respondents rate their confidence in making environmentally friendly choices on a scale from "Very Poor" to "Excellent," the Weibull distribution can model the different confidence levels and highlight trends and patterns, as seen in Table 31. This ability to handle diverse data makes the Weibull distribution a valuable tool for analysing survey results with multiple response options, providing meaningful insights that can inform decision-making and strategy development.

Table 29 outlines the analysis of normal distribution parameters applied to the survey data, offering another perspective on how biases shape decision-making. By providing the mean and standard deviation for each key variable, this table allows for a comparison between normally distributed responses and those modelled using other distributions, such as the Weibull. This comparative analysis enriches the overall understanding of how different statistical models can be used to measure and mitigate cognitive biases in sustainable decision-making.

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Table 29. Normal distribution parameter analysis

Monte Carlo question #	Mean	Standard deviation
1	0.99	0.11
2	0.99	0.11
3	0.19	0.39
4	0.65	0.48
5	2.39	0.72
6	2.39	0.83
7	1.76	1.31
8	3.15	0.76
9	3.14	0.92
10	2.25	0.93
11	2.97	0.94
12	3.33	0.81
13	1.65	1.20
14	3.32	0.77
15	3.33	0.76
16	3.23	0.86
17	3.06	1.00
18	3.06	0.82
19	3.16	0.83

- Simulation: Monte Carlo simulations are conducted using the estimated parameters to generate a distribution of possible survey outcomes.

The Monte Carlo simulation method generated 1000 iterations for each survey question using the Weibull distribution parameters. After that, the researcher employed the Normal distribution for a more precise representation.

Using the normal distribution parameters, the Monte Carlo simulation method generated 5000 iterations for each survey question. This approach allowed the researcher to estimate the distribution parameters and understand the variability within the dataset. The researcher calculated the mean (μ) and standard deviation (σ) for each question's response distribution, which are the Normal distribution parameters (Anastasiou et al., 2020:237-251). The fitting process was evaluated using goodness-of-fit tests and visual inspections of the probability density functions (Yousof et al., 2023:1308).

- Analysis:
    a. Analysis of the Weibull simulated results to understand the distribution and variability of the survey responses. All the following figures are Monte Carlo simulation results.

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Question 1:

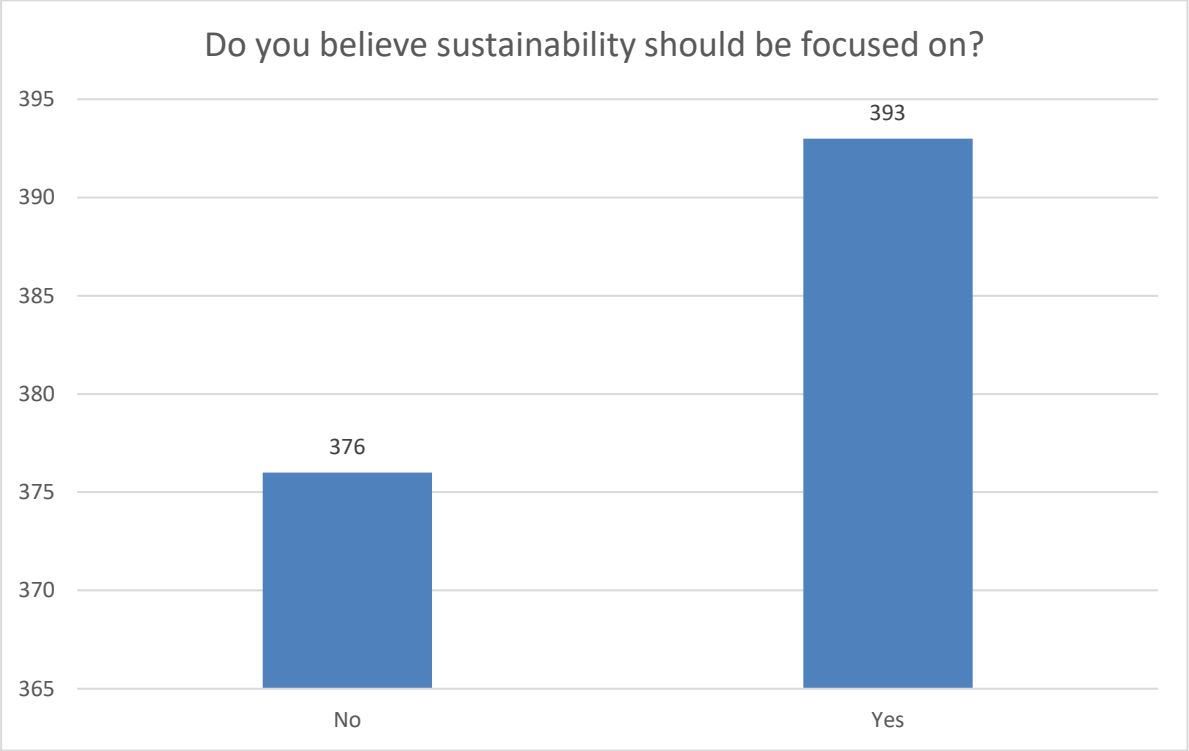

Figure 73. Question 1 - Weibull simulations

The proportion of "Yes" responses is seen in Figure 73:
The Monte Carlo simulation proportion of "Yes" responses is 393/376+393≈0.5115

Actual survey proportion:
The actual average of 0.9873 indicates a proportion of "Yes" responses close to 1, as 1 represents "Yes" and 0 means "No" in the survey data. The median and mode being one further indicate that most responses are "Yes".

Standard deviation and confidence interval:
The standard deviation of 0.1118 in the survey data suggests relatively low variability around the mean. The confidence interval (0.9627 - 1.0120) indicates that the "Yes" response proportion is consistently high, nearly 1.

Fit analysis:
The Monte Carlo simulation results do not fit well with the survey results for Question 1. The simulation shows a nearly equal split between "Yes" (0.5115) and "No" responses, while the actual survey results indicate a predominant "Yes" response (average 0.9873, median 1, mode 1).

Possible reasons for the discrepancy:

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Bias in simulation parameters: The parameters used in the Monte Carlo simulation have been set by the researcher to produce a more balanced distribution for this simulation iteration, whereas the survey data shows a strong bias towards "Yes".

Distribution assumption: The assumption of the distribution for the Monte Carlo simulation might not match the actual distribution of responses, which appears to be heavily skewed towards "Yes".

Sample size and variability: The actual sample size and how variability is accounted for in the simulation might differ from the real-world data.

The Monte Carlo simulation results show a significant deviation from the actual survey results for Question 1. The survey data is heavily skewed towards "Yes" responses, while the simulation suggests a more balanced response. Adjusting the simulation parameters to reflect better the observed distribution in the survey data would be necessary to achieve a more accurate fit.

Question 2:

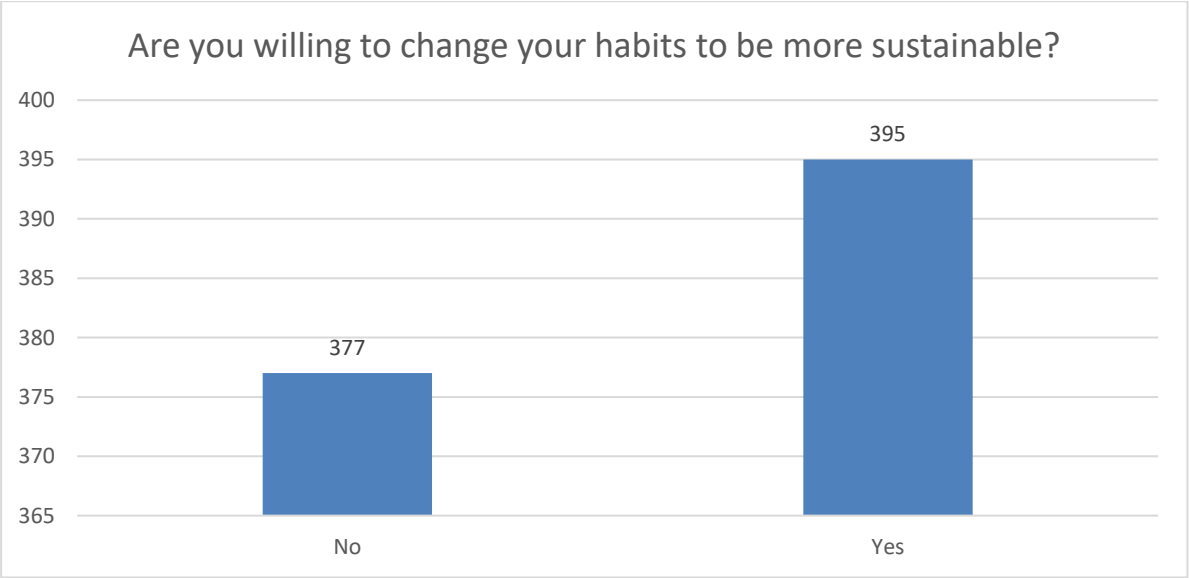

Figure 74. Question 2 - Weibull simulations

The proportion of yes responses is seen in Figure 74:
The Monte Carlo simulation proportion of "Yes" responses is 395/377+395≈0.5118

Actual survey proportion:
The actual average of 0.9873 indicates a proportion of "Yes" responses close to 1, as 1 represents "Yes" and 0 means "No" in the survey data. The median and mode being one further indicate that most responses are "Yes".

Standard deviation and confidence interval:

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The standard deviation of 0.1118 in the survey data suggests relatively low variability around the mean. The confidence interval (0.9627 - 1.0120) indicates that the "Yes" response proportion is consistently high, nearly 1.

Fit analysis:
The Monte Carlo simulation results do not fit well with the survey results for Question 2. The simulation shows a nearly equal split between "Yes" (0.5118) and "No" responses, while the actual survey results indicate a predominant "Yes" response (average 0.9873, median 1, mode 1).

Possible reasons for the discrepancy:
Bias in simulation parameters: The parameters used in the Monte Carlo simulation may have been set to produce a more balanced distribution, whereas the survey data shows a strong bias towards "Yes".

Distribution assumption: The assumption of the distribution for the Monte Carlo simulation might not match the actual distribution of responses, which appears to be heavily skewed towards "Yes".

Sample size and variability: The actual sample size and how variability is accounted for in the simulation might differ from the real-world data.

The Monte Carlo simulation results show a significant deviation from the actual survey results for Question 2. The survey data is heavily skewed towards "Yes" responses, while the simulation suggests a more balanced response. Adjusting the simulation parameters to reflect better the observed distribution in the survey data would be necessary to achieve a more accurate fit.

Question 3:

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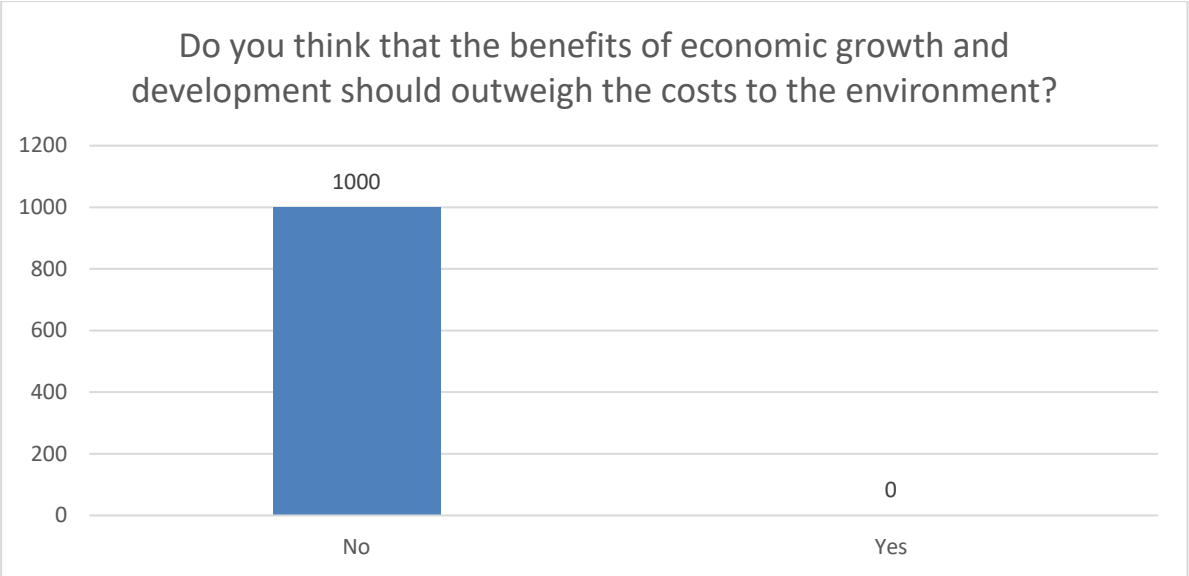

Figure 75. Question 3 - Weibull simulations

The proportion of yes responses is seen in Figure 75:
The Monte Carlo simulation proportion of "Yes" responses is 0/1000+0=0

Actual survey proportion:
The actual average of 0.1899 indicates a proportion of "Yes" responses close to 0.19, as 1 represents "Yes" and 0 means "No" in the survey data. The median and mode being 0 further indicate that most responses are "No".

Standard deviation and confidence interval:
The standard deviation of 0.3922 in the survey data suggests moderate variability around the mean. The confidence interval (0.1034 - 0.2764) indicates that the proportion of "Yes" responses falls within this range.

Fit analysis:
The Monte Carlo simulation results fit well with the survey results for Question 3. The simulation and the survey indicate a predominant "No" response.

Possible reasons for consistency:
Accurate simulation parameters: The parameters used in the Monte Carlo simulation likely align well with the actual distribution of responses, showing a predominant "No" response.

Distribution assumption: The assumption of the distribution for the Monte Carlo simulation matches the actual distribution of responses, which is heavily skewed towards "No".

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Sample size and variability: The actual sample size and how variability is accounted for in the simulation reflect the real-world data accurately.
The Monte Carlo simulation results are a good fit with the survey results for Question 3. The simulation and survey data indicate a predominant "No" response. The simulation accurately represents the observed distribution in the survey data.

Question 4:

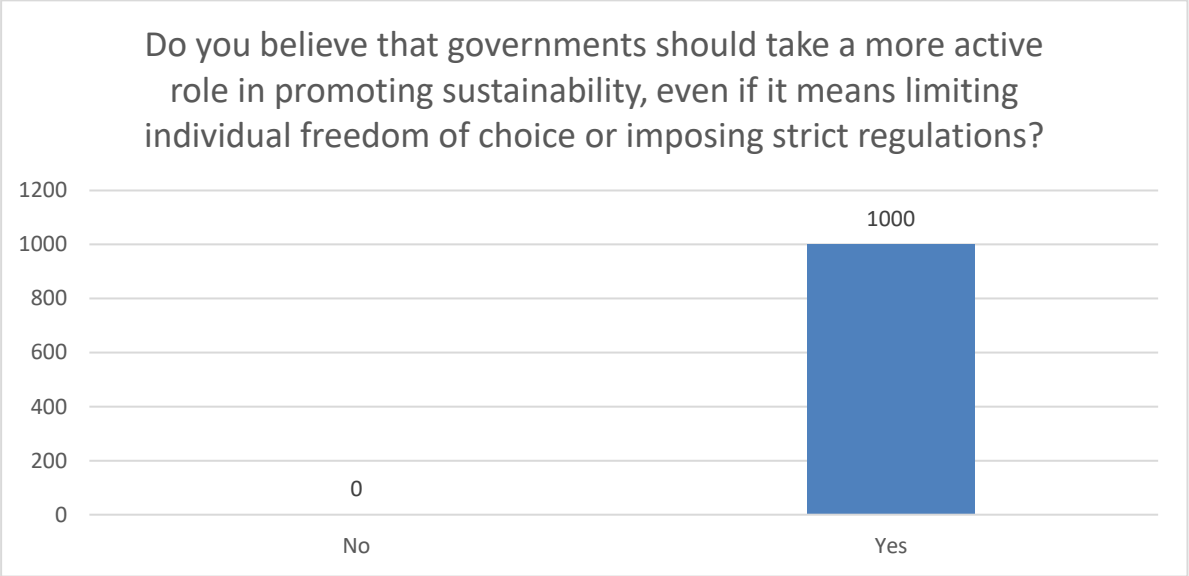

Figure 76. Question 4 - Weibull simulations

For Question 4, the Monte Carlo simulation results show 0 No and 1000 Yes responses, as seen in Figure 76. Here is a detailed comparison with the actual survey data.

Average and median:
The actual survey average (0.64556962) indicates that the majority of responses are closer to Yes (1) than No (0). The median and mode further confirm that most respondents answered Yes.

Standard deviation:
The standard deviation of 0.478340345 reflects some variability in the responses, suggesting not all were Yes, though the majority were.

Confidence interval:
The 95% confidence interval [0.540089271, 0.751049969] shows that the average response is significantly above 0.5, leaning towards Yes.

Monte Carlo results:
The simulation results with 100% Yes responses align with the tendency of the actual data, which has a high average, median, and mode, indicating a solid skew towards

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Yes. However, the Monte Carlo simulation does not capture the variability in the actual responses, where some No responses were present, as evidenced by the standard deviation.

Fit assessment:
The Monte Carlo results fit well with the actual data regarding the overall trend (most respondents answered Yes). The fit does not reflect the variability (presence of some No responses) seen in the data, as indicated by the non-zero standard deviation. The simulation accurately mirrors the central tendency but oversimplifies the response distribution by not accounting for the observed variability.

While the Monte Carlo results reflect the dominant trend towards Yes, they lack the granularity to capture the entire distribution of responses, precisely the occasional No reactions present in the actual data.

Question 5: How informed are you about sustainability issues? The graph for this question shows the distribution of respondents' self-assessed knowledge about sustainability. The Weibull distribution is used to model the probability density, with the X-axis representing the level of expertise and the Y-axis showing the probability density. This graph helps understand the respondents' overall awareness of sustainability issues.

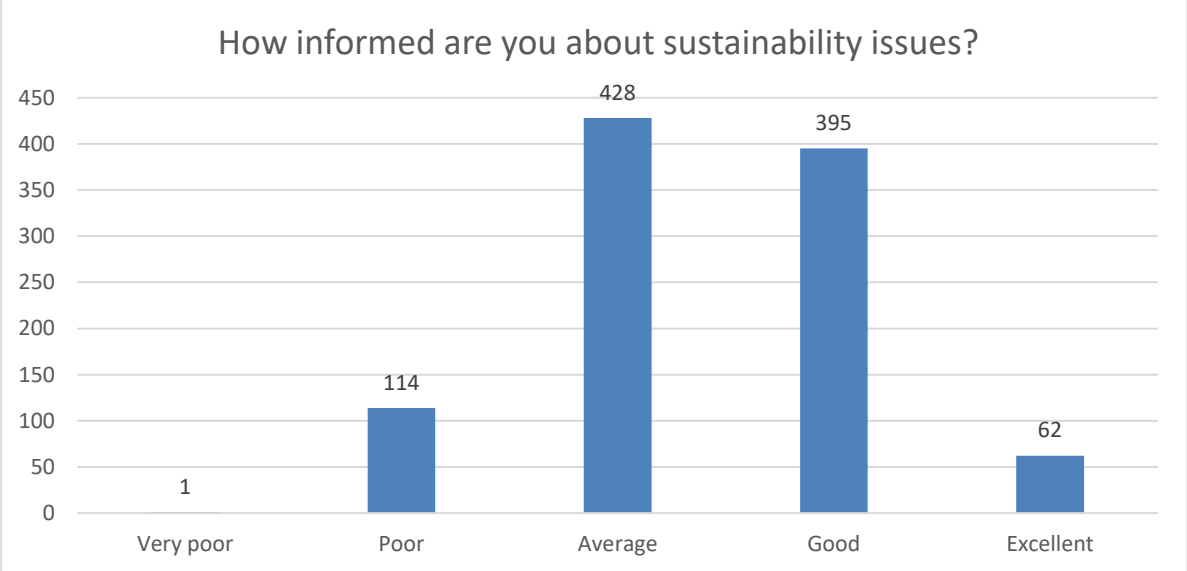

Figure 77. Question 5 - Weibull simulations

The average rating is approximately 2.39 (between Average and Good), with a standard deviation of 0.72, as seen in Figure 77. This fits well with the survey results, showing a high concentration of responses around Average and Good.

Question 6: How confident are you in making environmentally friendly choices daily? This graph illustrates the distribution of respondents' confidence in making

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environmentally friendly choices. The Weibull distribution models the probability density, providing insights into how confident individuals feel about their environmental decisions.

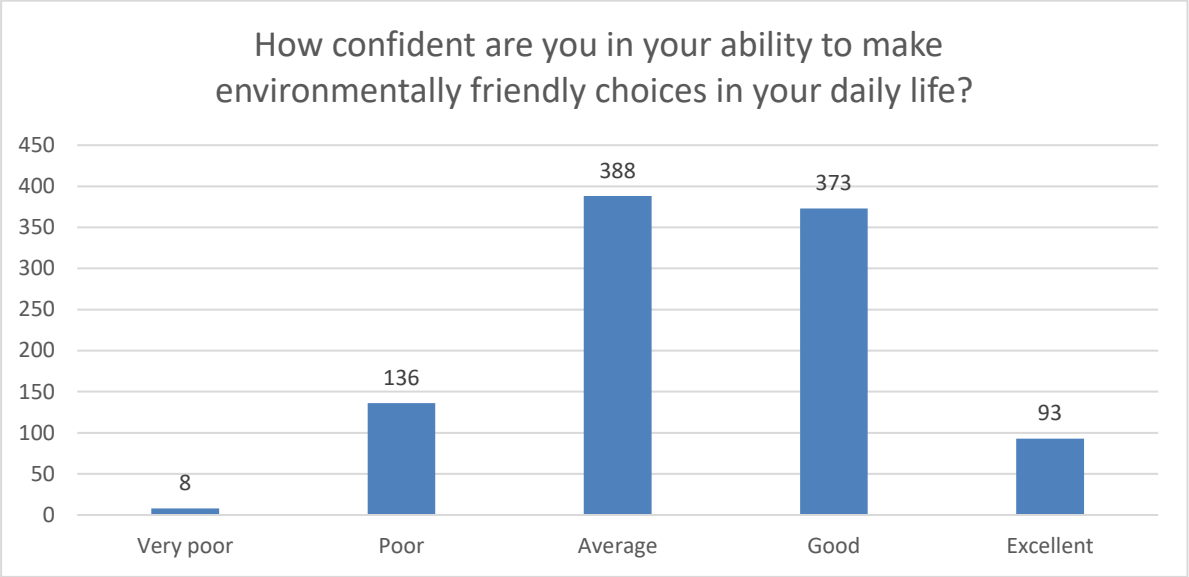

Figure 78. Question 6 - Weibull simulations

The average rating is approximately 2.39 (between Average and Good), with a standard deviation of 0.83, as seen in Figure 78. This fits well with the survey results, reflecting a solid confidence level predominantly around Average and Good.

Question 7: Would you spend more money to buy repaired, re-used, or recycled products than new ones? The graph for this question uses the Weibull distribution to model the likelihood of respondents spending more on sustainable products. The X-axis represents the likelihood, and the Y-axis shows the probability density. This helps understand consumer willingness to invest in sustainable products.

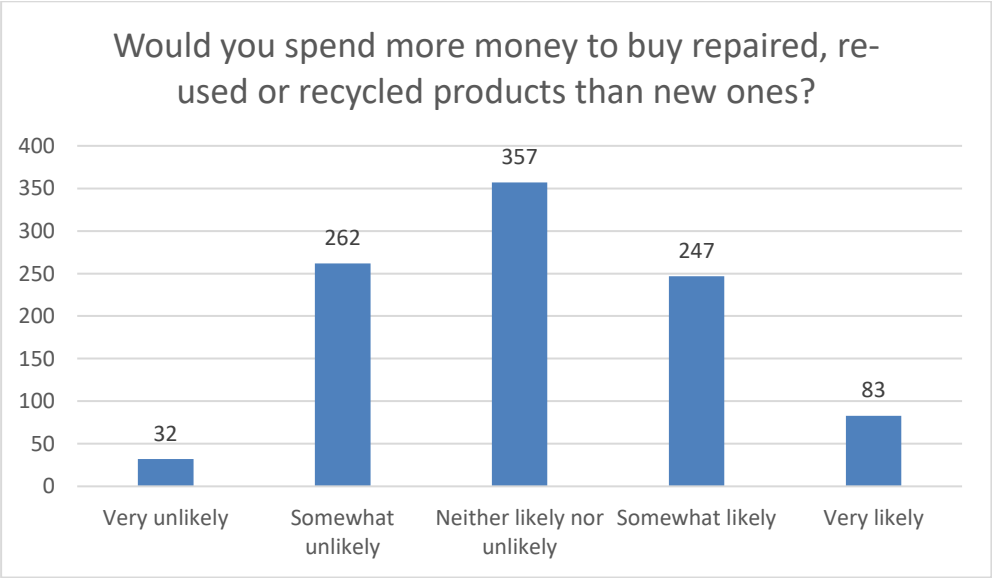

Figure 79. Question 7 - Weibull simulations

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The average rating is approximately 1.76 (closer to Somewhat unlikely), with a standard deviation of 1.31, as seen in Figure 79. This distribution shows a wide range, aligning with the actual survey's broad spread of responses.

Question 8: How willing are you to change your lifestyle or consumption habits to support sustainability and protect the environment? This graph models the willingness of respondents to change their lifestyle for sustainability, as seen in Figure 80. The Weibull distribution is used to analyse the probability density of different levels of willingness, providing a clear picture of respondents' readiness to adopt sustainable practices.

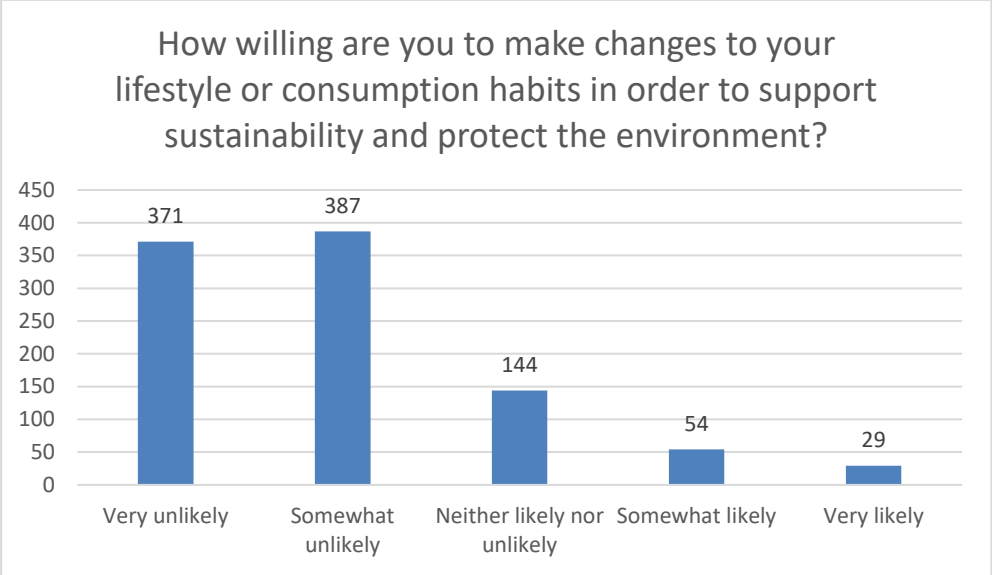

Figure 80. Question 8 - Weibull simulations

The Monte Carlo simulation results differ significantly from the actual survey data. The actual data shows most responses in the "Very unlikely" and "Somewhat unlikely" categories, whereas the Monte Carlo results indicate a more optimistic distribution. This discrepancy may arise from the difference in underlying distributions in the Monte Carlo simulation.

Question 9: How much do you believe that cognitive biases can impact the success or failure of CE initiatives? The graph for this question shows the distribution of beliefs regarding the impact of cognitive biases on CE initiatives, as seen in Figure 81. The Weibull distribution is applied to model the probability density, highlighting how strongly respondents feel about the role of cognitive biases in these initiatives.

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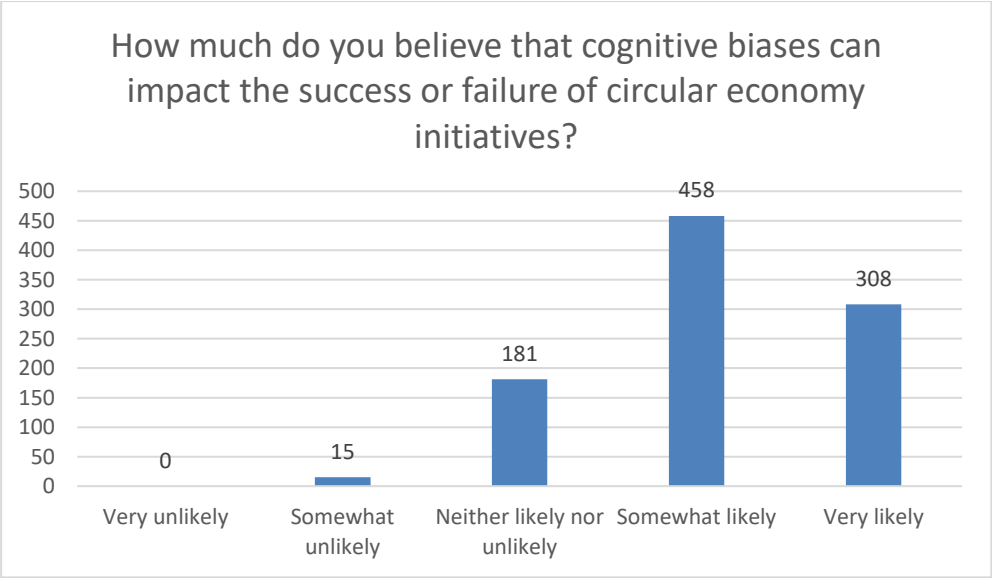

Figure 81. Question 9 - Weibull simulations

The average rating is approximately 3.14 (between Somewhat likely and Very likely), with a standard deviation of 0.92. This closely aligns with the survey responses, showing a strong belief in the impact of cognitive biases.

Question 10: How often do you try to reduce your carbon footprint or limit your use of single-use plastics?

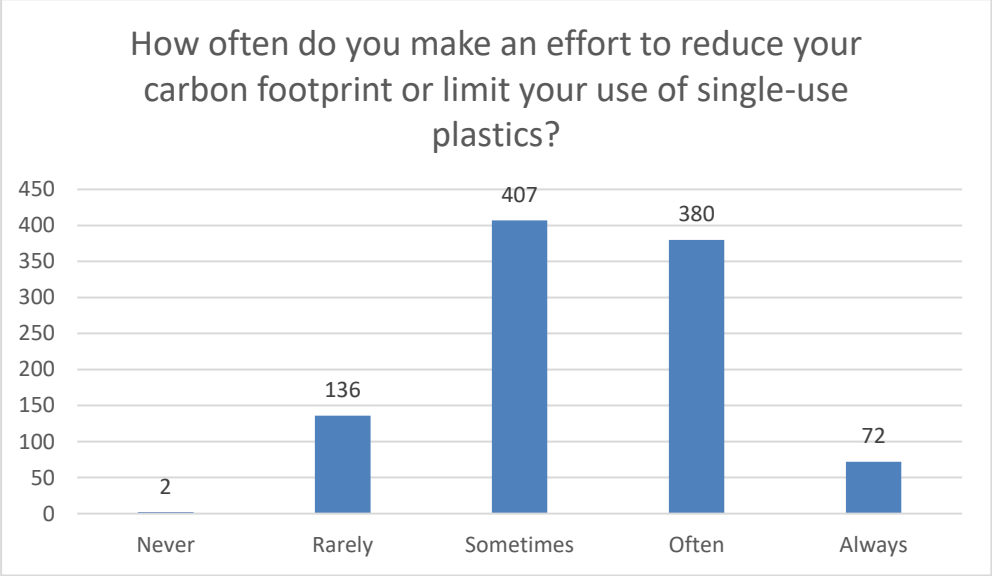

Figure 82. Question 10 - Weibull simulations

This graph depicts the frequency of efforts made by respondents to reduce their carbon footprint, as seen in Figure 82. The Weibull distribution models the probability density, showing how often respondents engage in environmentally friendly practices. The average rating is approximately 2.25 (between Sometimes and Often), with a standard deviation of 0.93. This fits well with the survey responses, indicating a frequent effort to reduce carbon footprints.

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Question 11: Do you agree that reducing the use of fossil fuels in our daily lives is imperative by increasing the demand for sustainable products? This graph uses the Weibull distribution to model the agreement levels with the statement about reducing fossil fuel use, as seen in Figure 83. The X-axis represents the agreement levels, and the Y-axis shows the probability density.

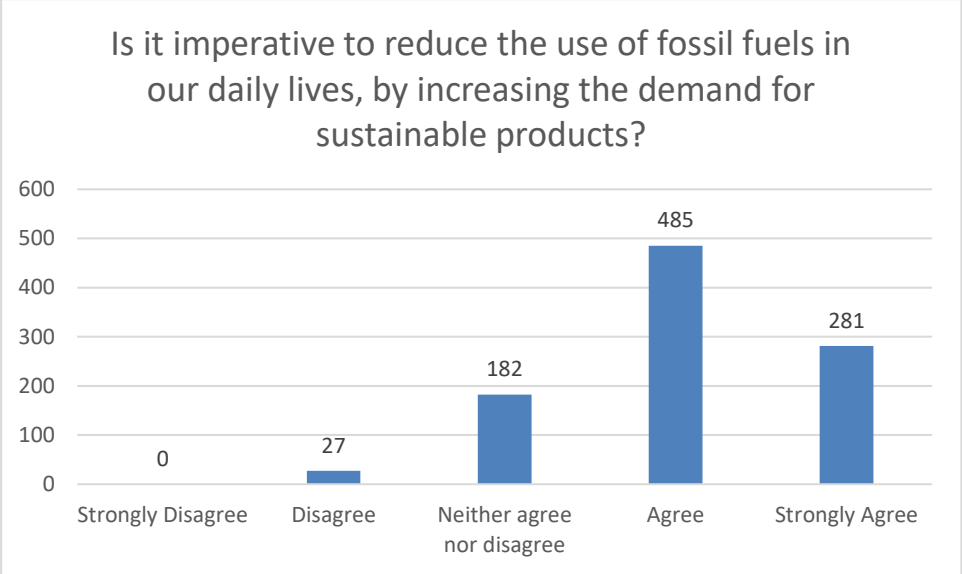

Figure 83. Question 11 - Weibull simulations

The average rating is approximately 2.97 (closer to Agree), with a standard deviation of 0.94. This fits well with the actual survey results, showing a solid agreement with the importance of reducing fossil fuel use

Question 12: Do you agree that it is essential that society follows environmentally friendly practices? The graph for this question models the distribution of agreement levels regarding the importance of following ecologically friendly practices, as seen in Figure 84. The Weibull distribution helps understand the consensus among respondents.

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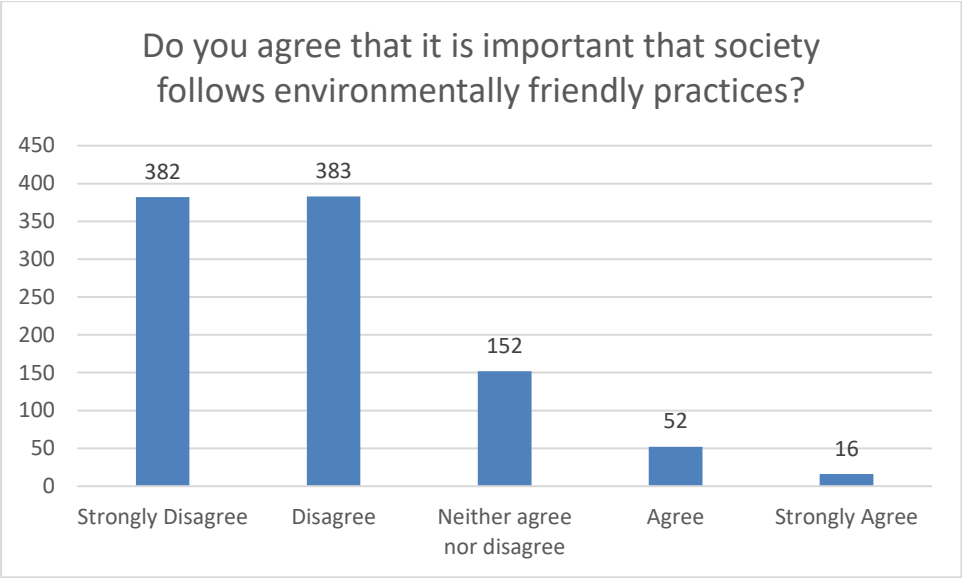

Figure 84. Question 12 - Weibull simulations

The survey data has a high average score (3.33), indicating a general agreement with the importance of environmentally friendly practices. The median and mode are both 3, which further supports this trend.

The Weibull distribution data shows many respondents strongly disagree (382) or disagree (383) with the statement, which starkly contrasts the survey data indicating a general agreement. The Weibull distribution might not be the best fit for this question, as it tends to model failure times or life data, which may not align well with opinion-based survey data. A normal distribution might better capture the central tendency observed in the survey results.

Question 13: Do you agree that there is no proper way to change the public's awareness of the need to establish a more sustainable reality? This graph shows the distribution of agreement levels with the statement about changing public awareness for sustainability, as seen in Figure 85. The Weibull distribution models the probability density to provide insights into respondents' beliefs.

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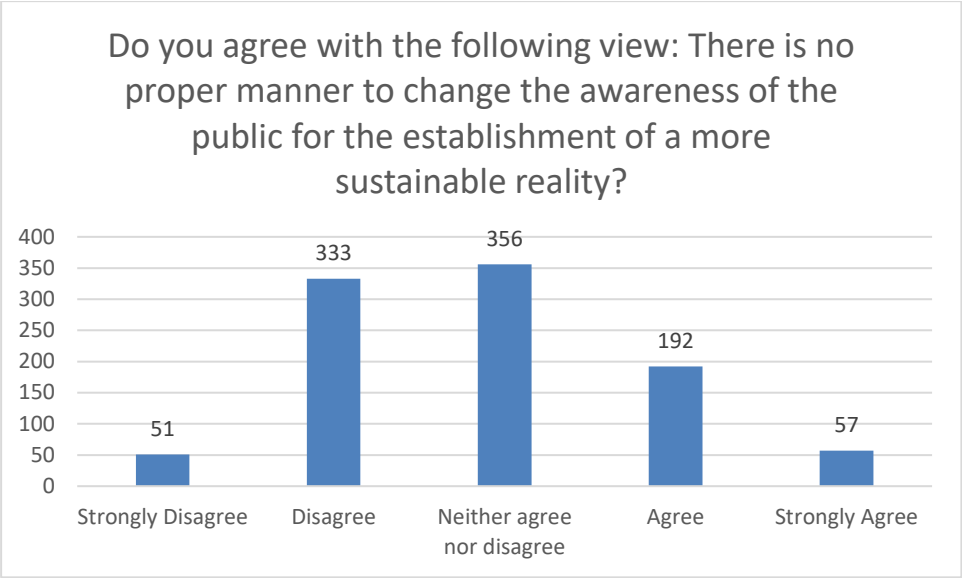

Figure 85. Question 13 - Weibull simulations

The average rating is approximately 1.65 (closer to Disagree), with a standard deviation of 1.20. This fits well with the survey results, showing a general disagreement with the statement.

Question 14: Do you think it is essential for individuals to take action to reduce their impact on the environment?

The graph for this question models respondents' importance on individual actions for environmental impact reduction, as seen in Figure 86. The Weibull distribution is used to analyse the probability density of agreement levels.

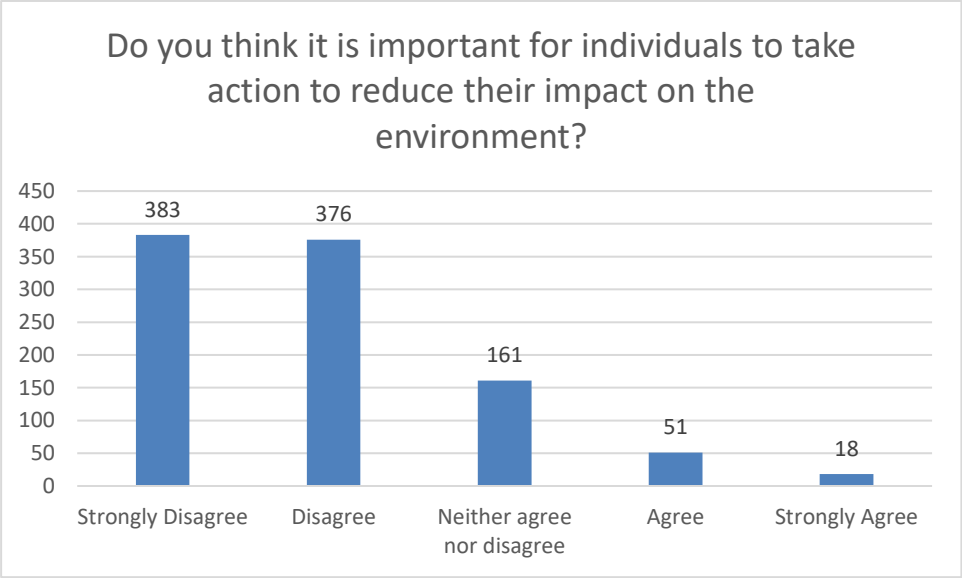

Figure 86. Question 14 - Weibull simulations

The average rating is approximately 3.32 (closer to Neither agree nor disagree), with a standard deviation of 0.77. This indicates a broad range of opinions, with many

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respondents disagreeing or strongly disagreeing. The survey data indicates a higher average and a mode of 4, suggesting that more respondents agree with the statement. The Weibull distribution data, however, shows a majority of responses in the "Strongly Disagree" and "Disagree" categories.

The Weibull distribution may not accurately capture the central tendency and actual responses' spread. A normal distribution might provide a better fit, aligning more closely with the exact average and standard deviation observed in the survey data.

Question 15: To what extent do you believe environmental problems can be solved through technology and innovation? This graph illustrates the distribution of beliefs about solving environmental problems through technology and innovation, as seen in Figure 87. The Weibull distribution provides a detailed understanding of respondents' views on technological solutions.

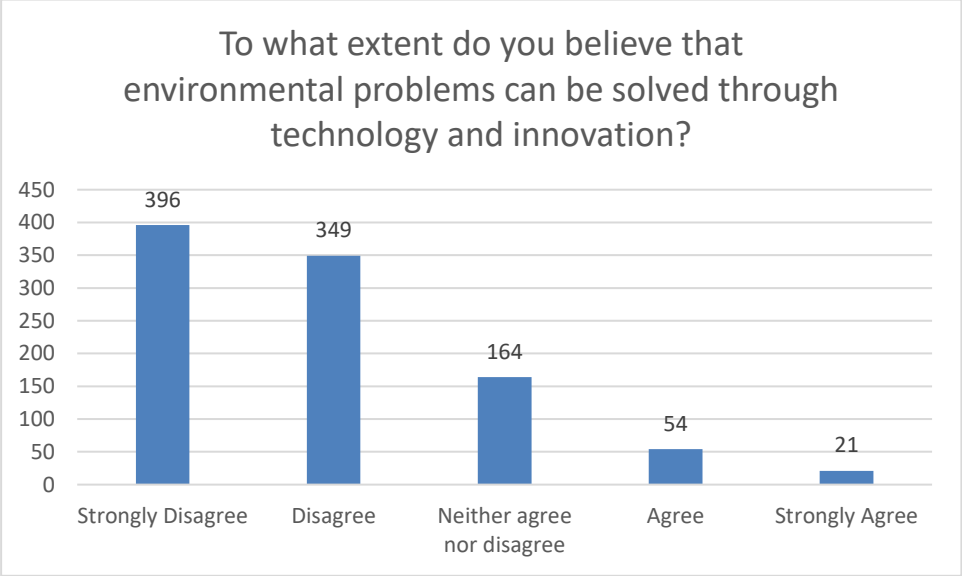

Figure 87. Question 15 - Weibull simulations

The average rating is approximately 3.33 (closer to Neither agree nor disagree), with a standard deviation of 0.75. This indicates a wide range of opinions, with many respondents disagreeing or strongly disagreeing. The survey data shows a higher level of agreement, with an average close to 3.33 and a mode of 3. The Weibull distribution data, however, has a significant number of responses in the "Strongly Disagree" and "Disagree" categories.

The Weibull distribution might not be suitable for modelling the central tendency and variability observed in the survey data. Using a normal distribution could better represent the actual responses.

Question 16: To what extent should businesses prioritise sustainability in their decision-making? The graph for this question models the extent to which respondents

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believe companies should prioritise sustainability, as seen in Figure 88. The Weibull distribution helps to understand the consensus on corporate responsibility for sustainability.

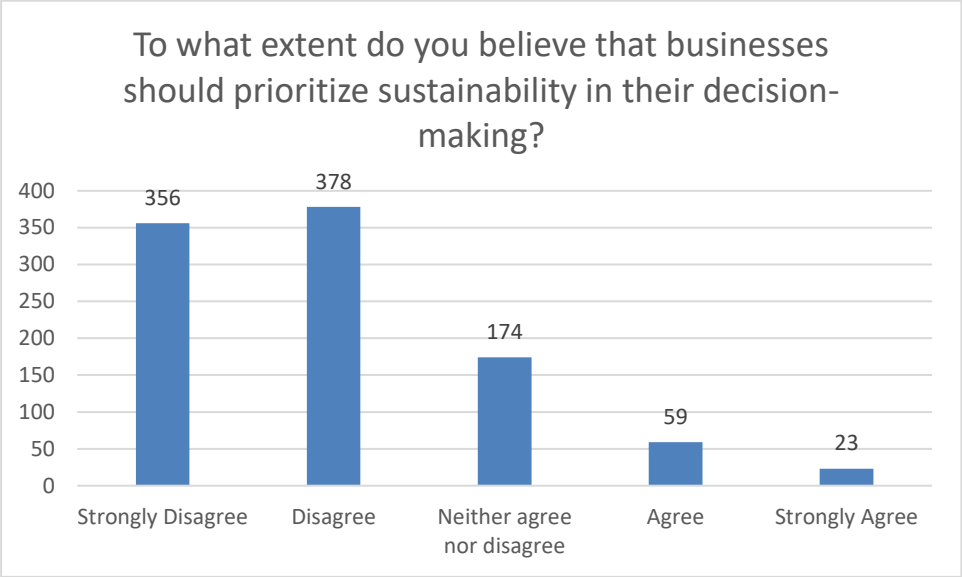

Figure 88. Question 16 - Weibull simulations

The average rating is approximately 3.23 (closer to Neither agree nor disagree), with a standard deviation of 0.85. This indicates a broad range of opinions, with many respondents disagreeing or strongly disagreeing. The actual survey data indicates a moderate level of agreement, with an average of 3.23 and a mode of 3. The Weibull distribution data shows more disagreement.

The actual survey responses might be better represented by a normal distribution, which can capture the central tendency and spread of the data more accurately than the Weibull distribution.

Question 17: To what extent do you think that climate change is caused by human activity? This graph shows the distribution of beliefs about the human causes of climate change, as seen in Figure 79. The Weibull distribution models the probability density, providing insights into respondents' views on climate change causation.

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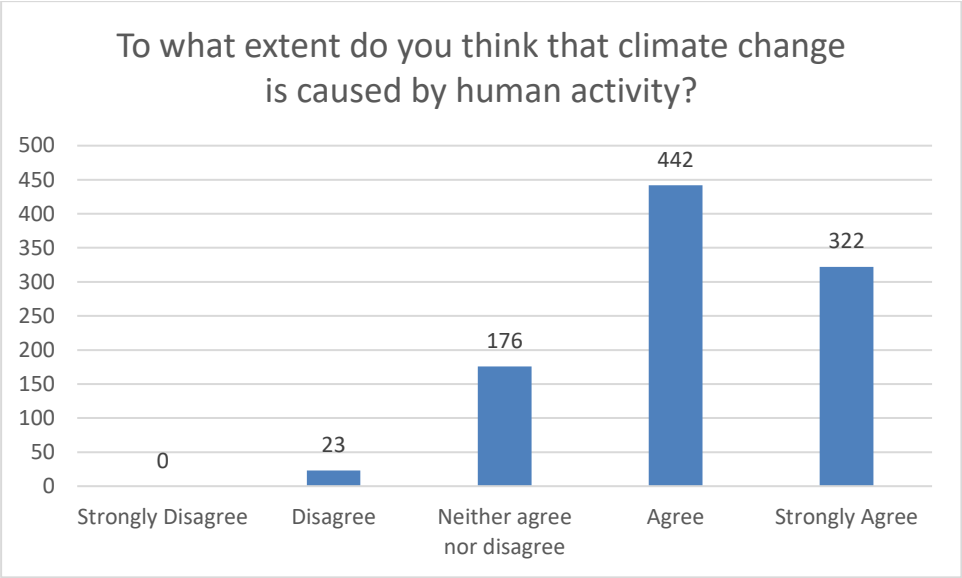

Figure 89. Question 17 - Weibull simulations

The average rating is approximately 3.06 (closer to Agree), with a standard deviation of 0.99. This fits well with the survey results, indicating a strong belief in human-caused climate change.

Question 18: To what extent do cognitive biases influence decision-making in adopting CE principles and practices? The graph for this question illustrates the distribution of beliefs regarding the influence of cognitive biases on decision-making for CE adoption, as seen in Figure 90. The Weibull distribution helps understand the perceived impact of cognitive biases.

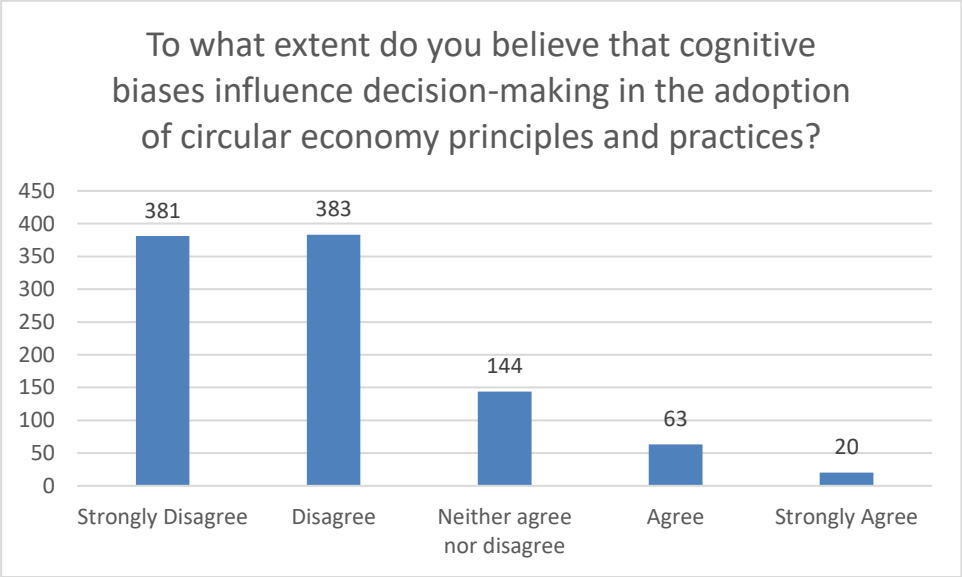

Figure 90. Question 18 - Weibull simulations

The average rating is approximately 3.06 (closer to Neither agree nor disagree), with a standard deviation of 0.82. The survey data suggests a moderate belief in the

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influence of cognitive biases, with an average of 3.06 and a mode of 3. The Weibull distribution data shows more disagreement.
A normal distribution could better capture the actual responses, which is more suited to modelling the central tendency and spread observed in the survey data.

Question 19: To what extent do you think cognitive biases play a role in resisting change and adopting CE practices? This graph models the distribution of beliefs about the role of cognitive biases in resistance to CE adoption, as seen in Figure 91. The Weibull distribution clearly shows respondents' views on this issue.

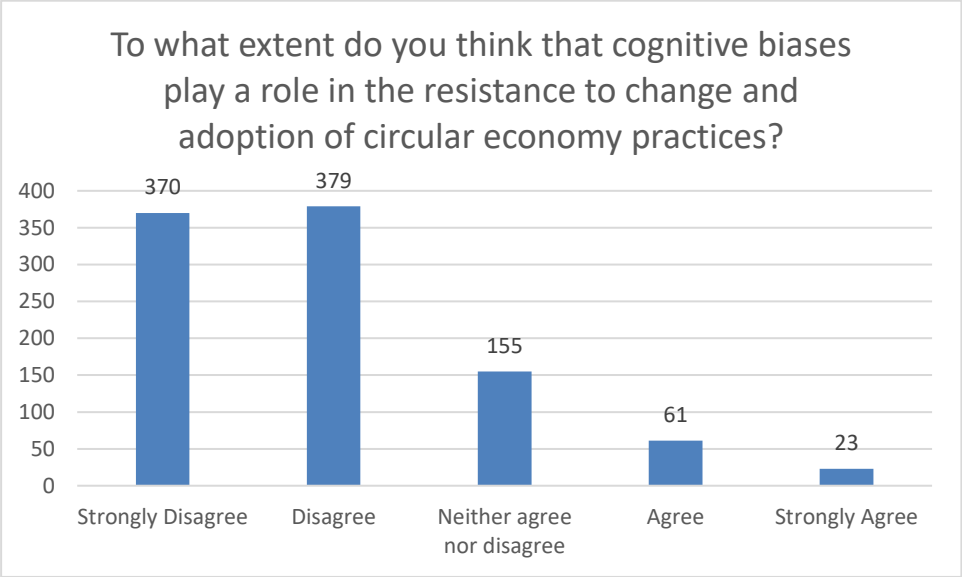

Figure 91. Question 19 - Weibull simulations

The average rating is approximately 3.16 (closer to Neither agree nor disagree), with a standard deviation of 0.83. The survey data indicates a moderate belief in the role of cognitive biases, with an average of 3.16 and a mode of 3. The Weibull distribution data shows more disagreement.

The actual survey responses may be better modelled using a normal distribution, which can more accurately reflect the central tendency and variability observed in the data.

For some of the analysed questions, the survey data suggests higher averages and modes that indicate more agreement with the statements than the Weibull distribution data. The discrepancies likely arise from the Weibull distribution's inability to accurately model the central tendency and spread of the actual survey responses (Abernethy, 2006). A normal distribution may provide a more accurate representation of the actual survey data.

b. Analysis of the Normal distribution simulated results to understand the distribution and variability of the survey responses.

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Question 1: The mean (0.99) and standard deviation (0.11) are almost identical for actual and Monte Carlo data. This suggests a good fit, as seen in Figure 92.

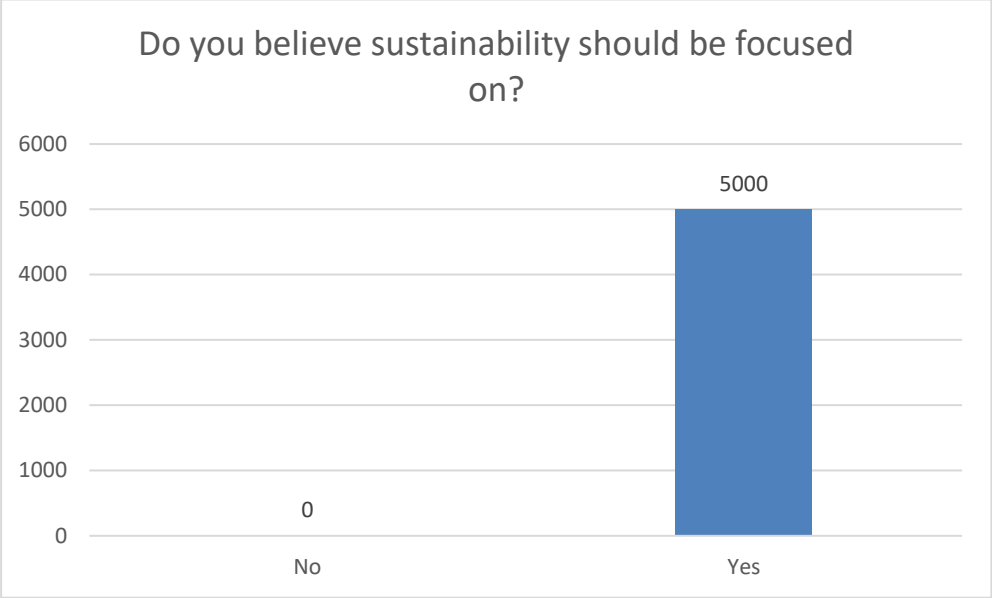

Figure 92. Question 1 - Normal distribution simulations

This strong match suggests that the Monte Carlo simulation accurately represents the central tendency and variability of responses for this question. The confidence intervals also overlap, confirming that the Monte Carlo model effectively captures the distribution of responses.

Question 2: The mean (0.99) and standard deviation (0.11) are almost identical for actual and Monte Carlo data. This suggests a good fit, as seen in Figure 93.

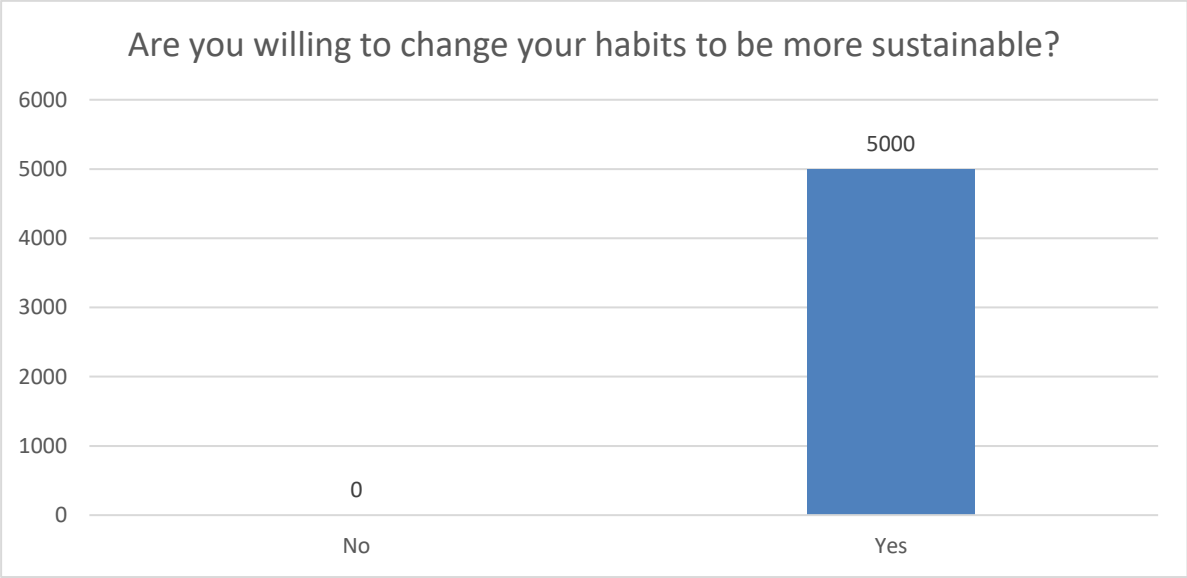

Figure 93. Question 2 - Normal distribution simulations

This indicates a high degree of accuracy in the Monte Carlo simulation for predicting the response distribution and variability for this question, reinforcing the consistency in the simulation's performance.

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Question 3: The actual survey mean of 0.19 aligns closely with the Monte Carlo mean of 0.19. The standard deviation in the Monte Carlo simulation (0.39) also matches the actual data's standard deviation (0.39) in Figure 94.

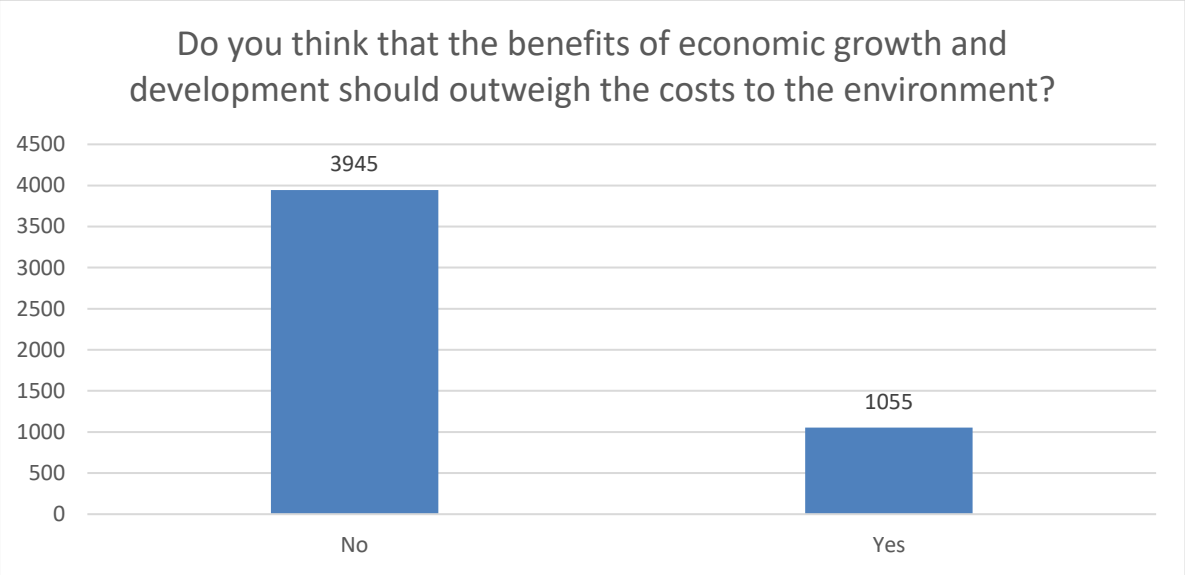

Figure 94. Question 3 - Normal distribution simulations

Question 4: The Monte Carlo simulation's mean and standard deviation are closely aligned with the actual data, with values of 0.65 and 0.48, respectively, as seen in Figure 95. This agreement indicates that the Monte Carlo model successfully mirrors the central tendency and spread of responses, providing a reliable representation of the survey data.

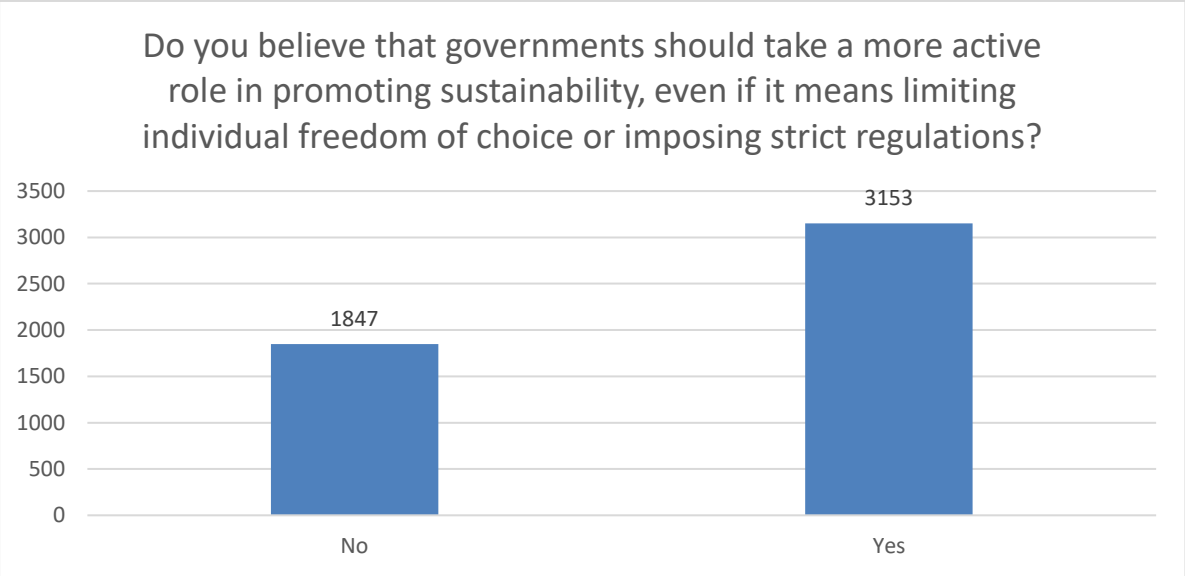

Figure 95. Question 4 - Normal distribution simulations

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Question 5: The survey mean of 2.39 matches the Monte Carlo mean precisely, and the standard deviation of 0.72 also aligns perfectly. This close match indicates that the Monte Carlo simulation is well-calibrated for capturing the response distribution and variability, providing a reliable approximation for this question, as seen in Figure 96.

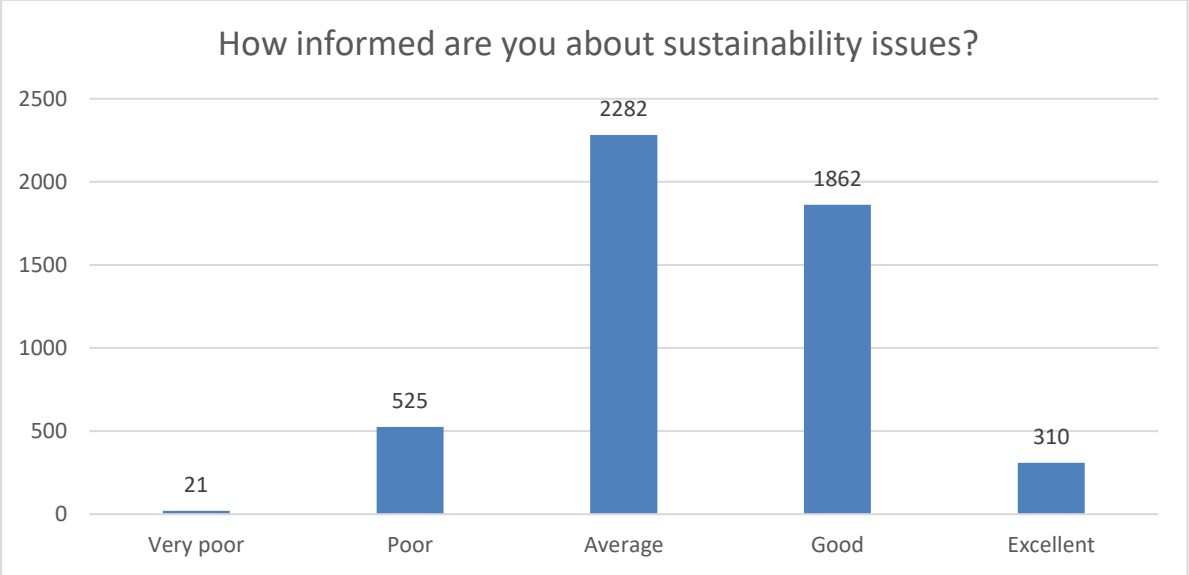

Figure 96. Question 5 - Normal distribution simulations

Question 6: The mean and standard deviation from the Monte Carlo simulation (2.39 and 0.83) closely match the actual data (2.39 and 0.83), as seen in Figure 97

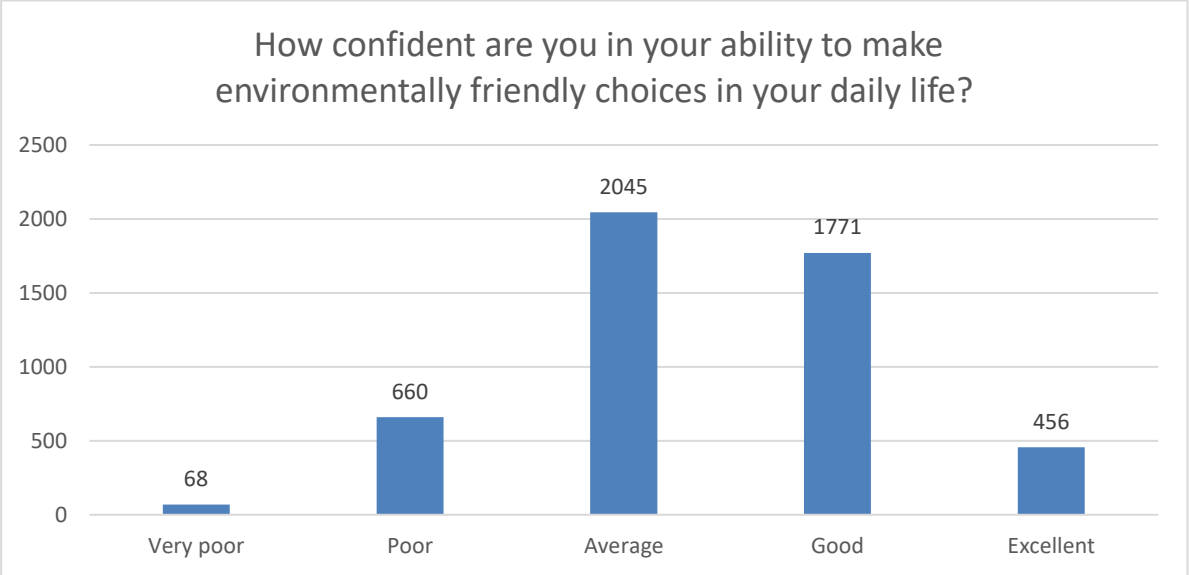

Figure 97. Question 6 - Normal distribution simulations

This suggests that the Monte Carlo simulation effectively represents the survey responses for this question, accurately reflecting the central tendency and the variability.

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Question 7: The mean is consistent between the actual data (1.76) and the Monte Carlo simulation (1.76). The standard deviation of 1.31 from the Monte Carlo model is the same as the actual data's standard deviation of 1.31, as seen in Figure 98.

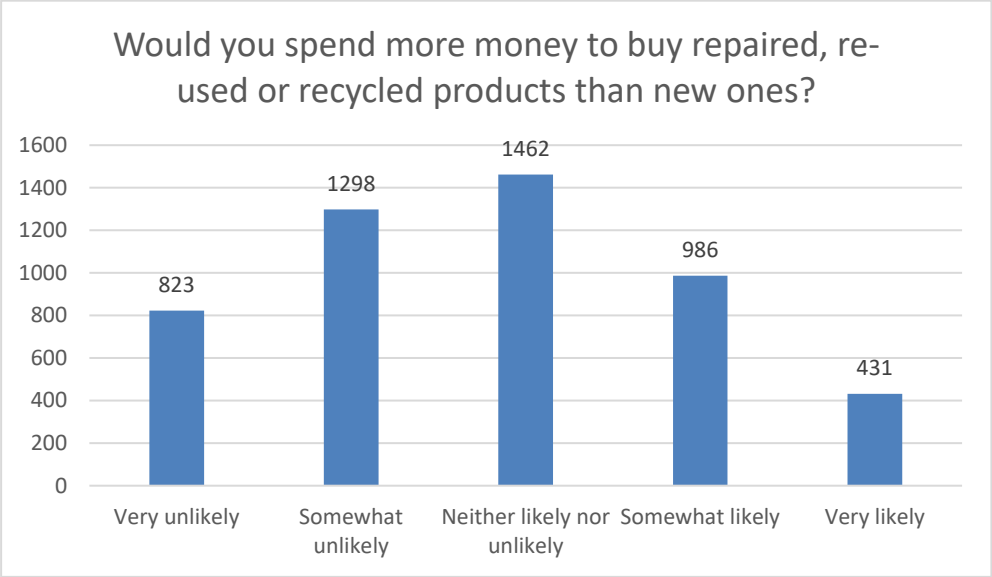

Figure 98. Question 7 - Normal distribution simulations

Question 8: The mean and standard deviation from the Monte Carlo simulation (3.15 and 0.76) closely match the actual data (3.15 and 0.76). This alignment demonstrates that the Monte Carlo model accurately reflects the response distribution and variability for this question, suggesting a high level of fit, as seen in Figure 99.

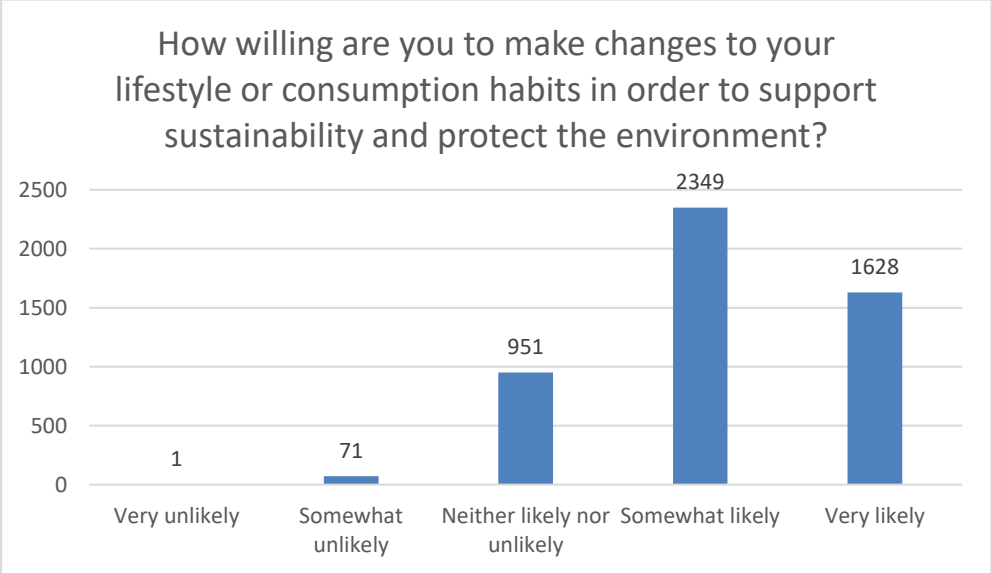

Figure 99. Question 8 - Normal distribution simulations

Question 9: The Monte Carlo values for Question 9 (mean of 3.14 and standard deviation of 0.92) closely match the actual data (mean of 3.14 and standard deviation of 0.92). This strong correlation indicates that the Monte Carlo simulation effectively

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captures both the central tendency and the variability of responses, ensuring a reliable representation of the actual survey data, as seen in Figure 100.

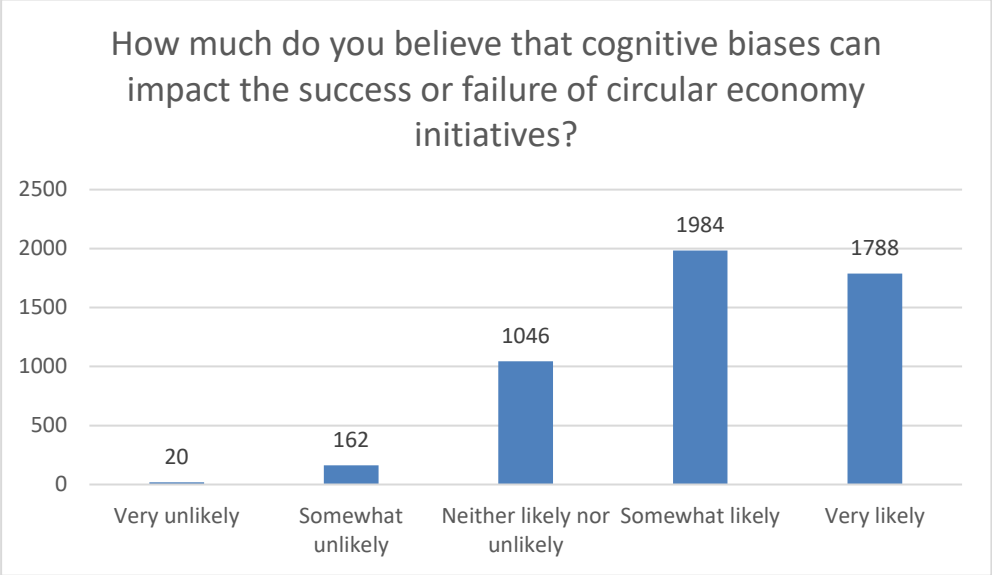

Figure 100. Question 9 - Normal distribution simulations

Question 10: The mean of 2.25 from the survey data for Question 10 aligns perfectly with the Monte Carlo mean of 2.25, and the standard deviation of 0.93 also matches closely. This suggests that the Monte Carlo simulation approximates this question's response distribution and variability, as seen in Figure 101.

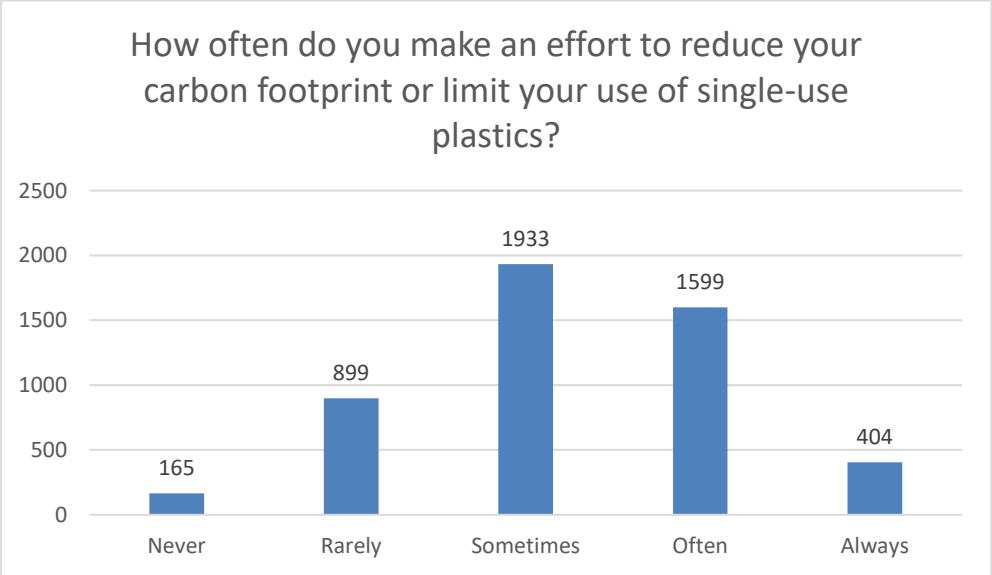

Figure 101. Question 10 - Normal distribution simulations

Question 11: The mean and standard deviation for Question 11 (2.97 and 0.94) are well-represented by the Monte Carlo simulation (mean of 2.97 and standard deviation of 0.94). This indicates that the Monte Carlo model accurately captures both the central

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tendency and the variability of responses, providing a reliable fit for this question, as seen in Figure 102.

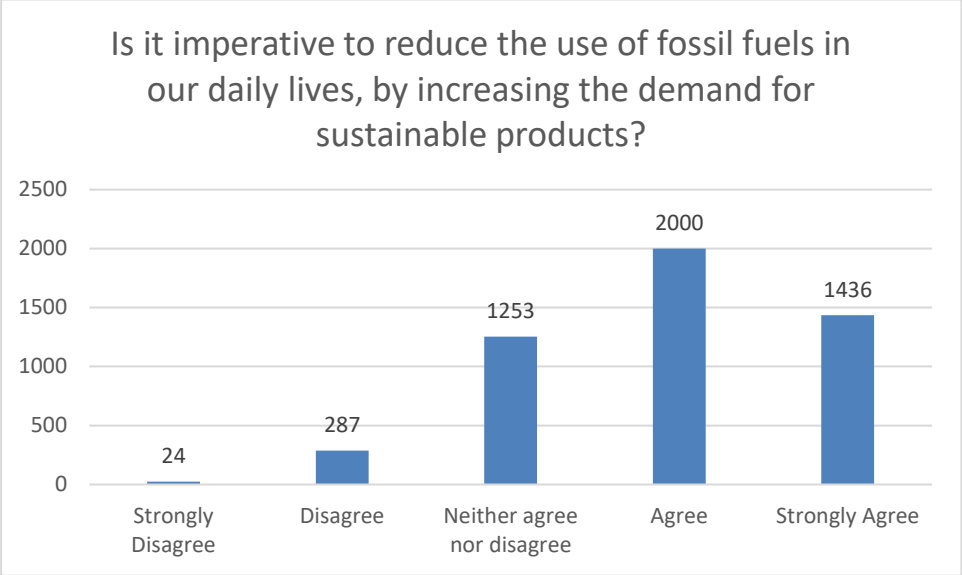

Figure 102. Question 11 - Normal distribution simulations

Question 12: The mean of 3.33 from the survey data matches the Monte Carlo mean precisely, and the standard deviation of 0.81 also aligns closely. This substantial agreement suggests that the Monte Carlo simulation effectively captures the response distribution and variability, reflecting the actual data well, as seen in Figure 103.

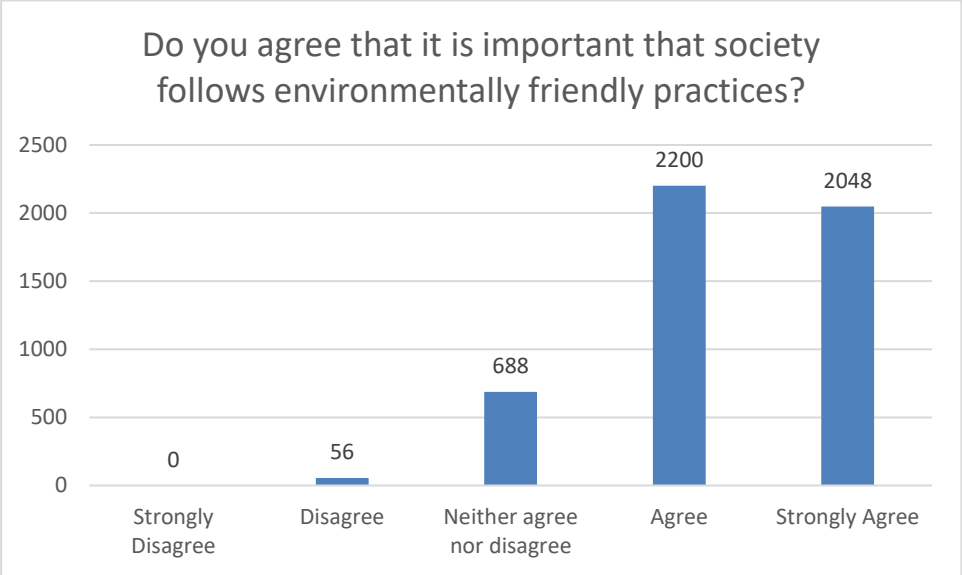

Figure 103. Question 12 - Normal distribution simulations

Question 13: The mean for Question 13 is consistent between the actual data (1.65) and the Monte Carlo simulation (1.65). The Monte Carlo standard deviation of 1.20 is the same as the actual data's standard deviation of 1.20. This indicates a good fit for the central tendency, as seen in Figure 104.

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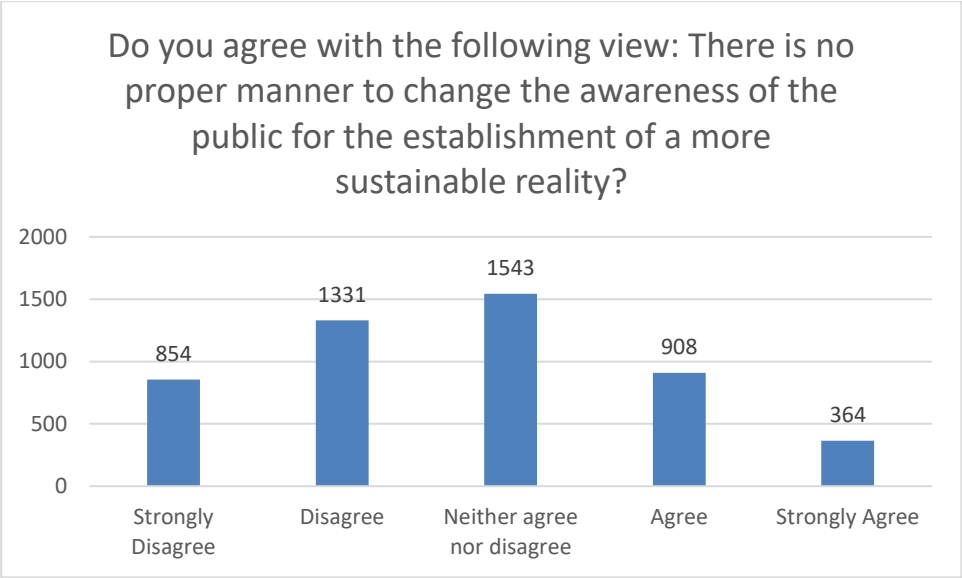

Figure 104. Question 13 - Normal distribution simulations

Question 14: The mean of 3.32 for Question 14 in the actual survey data and Monte Carlo simulation matches closely, as does the standard deviation of 0.77. This indicates that the Monte Carlo simulation accurately represents the central tendency and variability of responses for this question, as seen in Figure 105.

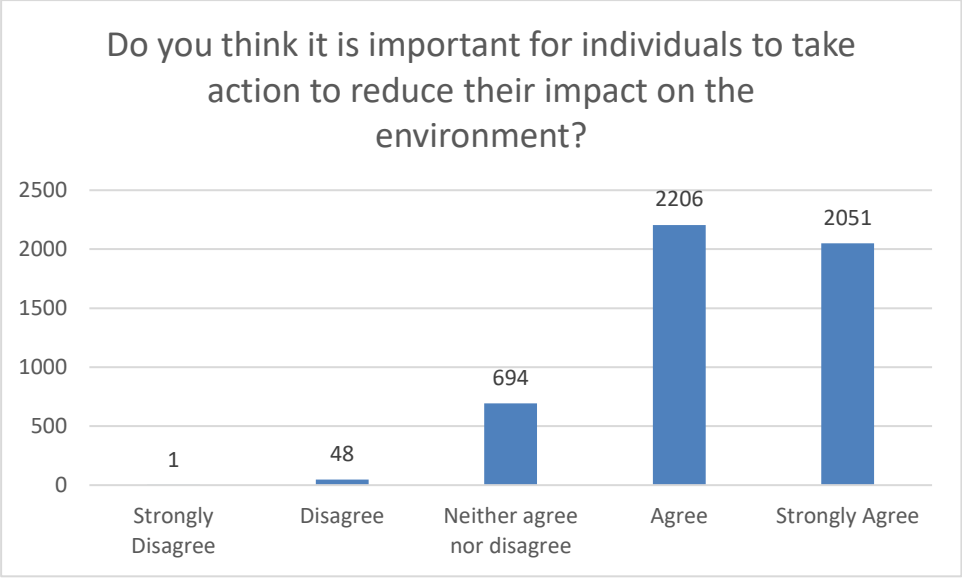

Figure 105. Question 14 - Normal distribution simulations

Question 15: Both the mean (3.33) and standard deviation (0.76) from the Monte Carlo simulation align well with the actual data (mean of 3.33 and standard deviation of 0.76). This demonstrates a firm fit, with the Monte Carlo simulation accurately reflecting the distribution and variability of responses, as seen in Figure 106.

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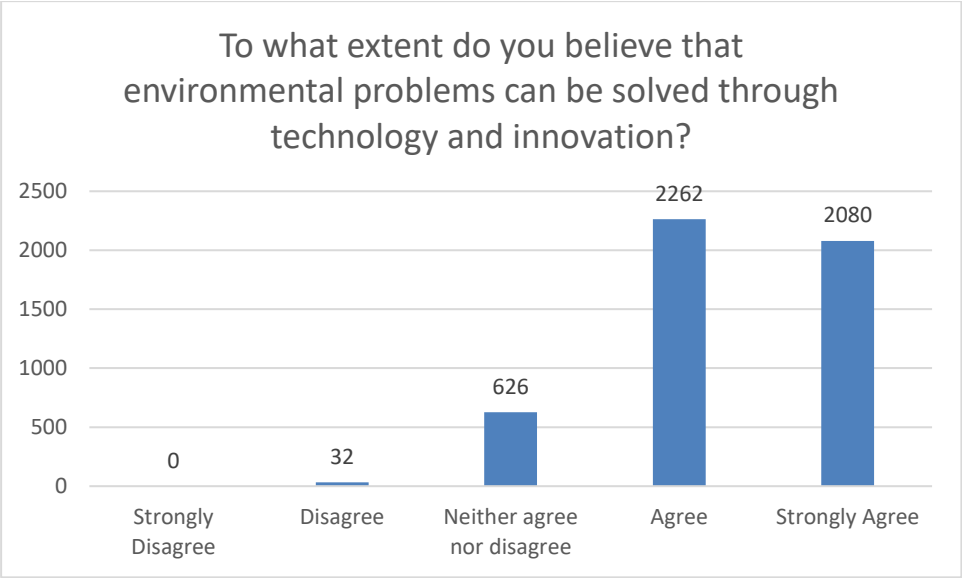

Figure 106. Question 15 - Normal distribution simulations

Question 16: The Monte Carlo simulation values for Question 16 (mean of 3.23 and standard deviation of 0.86) match the actual data (mean of 3.23 and standard deviation of 0.86). This suggests that the simulation effectively captures the central tendency and variability, providing a reliable approximation of the responses, as seen in Figure 107.

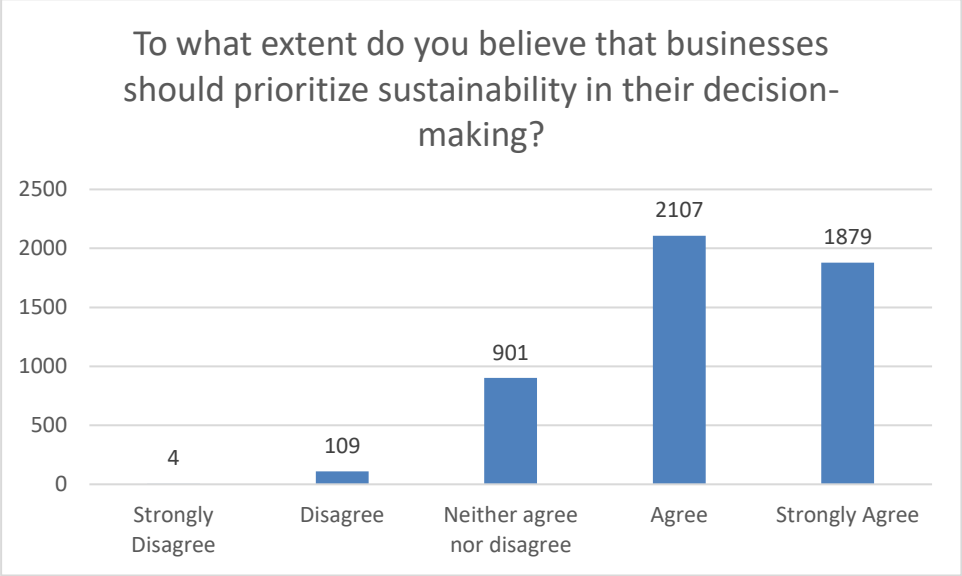

Figure 107. Question 16 - Normal distribution simulations

Question 17: the mean of 3.06 from the actual survey data is closely matched by the Monte Carlo mean of 3.06, and the standard deviation of 1.00 also aligns closely. This indicates that the Monte Carlo simulation effectively represents the response distribution and variability, as seen in Figure 108.

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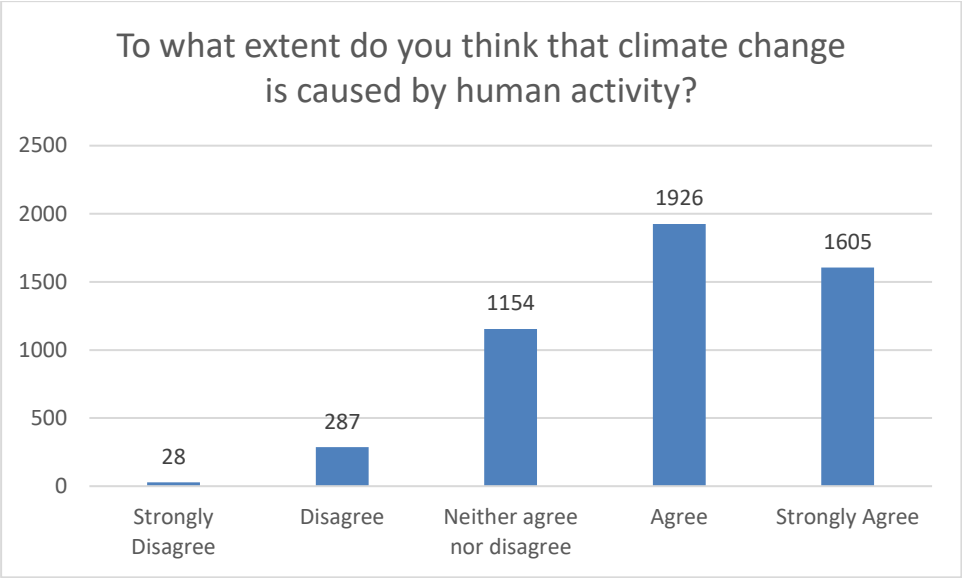

Figure 108. Question 17 - Normal distribution simulations

Question 18: The mean for Question 18 (3.06) matches closely with the Monte Carlo mean (3.06), and the standard deviation of 0.82 aligns well with the actual data's standard deviation. This demonstrates a good fit between the Monte Carlo simulation and the survey data, as seen in Figure 109.

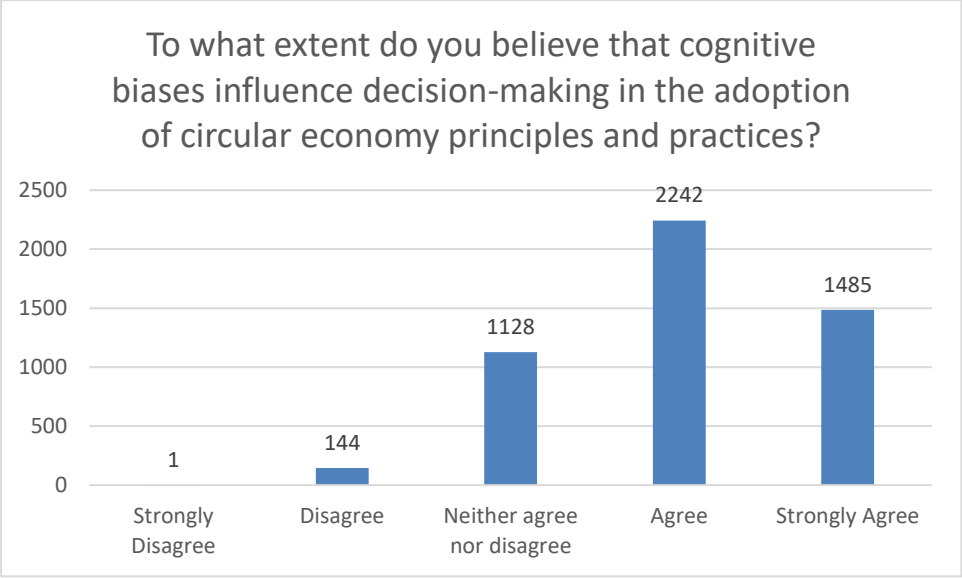

Figure 109. Question 18 - Normal distribution simulations

Question 19: The mean of 3.16 and standard deviation of 0.83 for Question 19 are closely aligned with the Monte Carlo values (mean of 3.16 and standard deviation of 0.83), as seen in Figure 110. This strong match indicates that the Monte Carlo simulation accurately reflects the responses' central tendency and variability.

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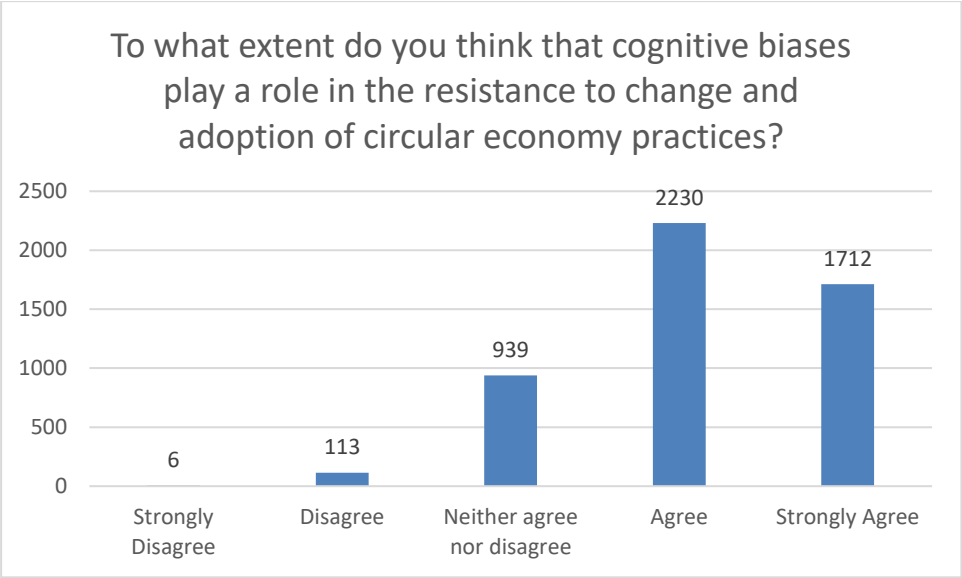

Figure 110. Question 19 - Normal distribution simulations

Overall, the Normal distribution Monte Carlo simulation fits the survey data reasonably well, particularly regarding means and standard deviations. However, there are some discrepancies in the variability (standard deviations) for specific questions. This might suggest that while the Monte Carlo simulation provides a good approximation, it may not capture all nuances of the data's variability or distribution.

7.2.3. Discussion

The application of Monte Carlo analysis combined with Weibull and normal distributions offers valuable insights into survey responses, particularly in understanding the variability and reliability of the data. The graphs for each question highlight critical aspects of the survey results, such as awareness levels, confidence in environmental choices, willingness to invest in sustainable products, and beliefs about the impact of cognitive biases.

The following figure summarises the mode of each survey answer versus the Weibull 2 parameter simulations and the normal distribution simulations.

Table 30. Comparison table between modes for Surveys, Monte Carlo Weibull and Normal distribution

Survey question #	Monte Carlo question #	Survey question: Mode	Monte Carlo question: Mode (Weibull)	Monte Carlo question: Mode (Normal)
2	1	1	0.51	1
7	2	1	0.51	1
8	3	0	0	0
9	4	1	1	1

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11.1	5	2	2.39	2
11.2	6	3	2.39	3
12.1	7	3	1.76	1
12.2	8	3	3.15	3
12.3	9	4	3.14	4
13	10	3	2.25	3
14.1	11	3	2.97	3
14.2	12	3	3.33	3
14.3	13	1	1.65	1
14.4	14	4	3.32	4
14.5	15	3	3.33	3
14.6	16	3	3.23	3
14.7	17	4	3.06	4
14.8	18	3	3.06	3
14.9	19	3	3.16	3

Table 31 summarises the results of the Monte Carlo analysis for each question and its corresponding distribution fit. By comparing the goodness-of-fit for both the Weibull and normal distributions across all survey questions, this table helps determine which distribution provides the most accurate representation of stakeholder behaviour. The insights drawn from this analysis are critical for validating the model and ensuring its predictive accuracy when applied to real-world CE decision-making scenarios.

Table 31. Monte Carlo analysis distribution fit summary

Best distribution fit	Monte Carlo question (survey question number)
2 parameter Weibull	3 (8); 5 (11.1); 6 (11.2) and 7 (12.1) 9 (12.3); 10 (13), 11 (14.1); 13 (14.3) and 17 (14.7)
Normal	1 (2); 2 (7); 4 (9); 8 (12.2); 12 (14.2); 14 (14.4); 15 (14.5); 16 (14.6); 18 (14.8) and 19 (14.9)

These insights are crucial for developing targeted strategies to promote sustainability and address cognitive biases in decision-making. By understanding the distribution of responses, policymakers and industry practitioners can better design interventions to foster a culture of sustainability and leverage cognitive biases for positive outcomes.

Monte Carlo analysis and Weibull/normal distributions are powerful tools for analysing survey quantitative results. They comprehensively understand the data's variability and reliability, supporting accurate decision-making. Applying these methods to survey data enhances the insights gained from the study, enabling the development of effective strategies and interventions for promoting sustainability and addressing cognitive biases in decision-making (Groves et al., 2009).

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When applied to survey results, Monte Carlo analysis provides a comprehensive understanding of uncertainty by providing a range of possible outcomes and their probabilities. Rather than relying on a single estimate, Monte Carlo simulations reveal the potential variability in the data, helping to assess the reliability and robustness of the survey findings. This uncertainty quantification is crucial for making informed decisions based on survey data, as it highlights the range of possible scenarios and their likelihoods.

Surveys often yield data that do not fit standard distribution shapes or involve complex variable interactions. Monte Carlo analysis excels in modelling such complexities by generating numerous scenarios that reflect different possible distributions. This ability to model complex scenarios is precious when traditional statistical methods may fall short. Using Monte Carlo simulations, researchers can gain insights into how various factors influence survey outcomes and how uncertainties propagate through the model, leading to a more nuanced understanding of the data.

One of the strengths of Monte Carlo analysis is its capability to improve predictive models. By running simulations to generate a wide range of possible outcomes, researchers can evaluate the accuracy and reliability of their predictive models. This approach enhances the predictive power of the models used in analysing survey results, providing a clearer picture of future trends and potential outcomes. Demonstrating the robustness of predictive models through Monte Carlo simulations adds credibility to the research findings and supports more reliable conclusions.

Monte Carlo simulations enable the exploration of various 'what-if' scenarios by adjusting parameters and assumptions within the models. This flexibility allows researchers to assess how different conditions might impact the survey results and evaluate their findings' sensitivity to changes in assumptions. By examining these scenarios, researchers can gain valuable insights into the stability and reliability of their results, providing a more comprehensive understanding of the factors influencing the survey data.

The probabilistic nature of Monte Carlo analysis supports better decision-making by offering a detailed view of potential risks and impacts. By incorporating Monte Carlo simulations into survey analysis, researchers can make more informed decisions based on a thorough assessment of uncertainties and possible outcomes. This approach enhances the quality of the conclusions drawn from the survey data, ensuring that decisions are based on a robust and well-rounded understanding of the data.

Monte Carlo analysis is also valuable for validating statistical models and tests. By simulating data under known conditions and comparing the results to theoretical

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predictions, researchers can verify the performance of their models and ensure their accuracy. This validation is essential for maintaining the integrity of statistical inferences drawn from survey data, reinforcing the validity and reliability of the research findings.

Incorporating Monte Carlo analysis into the examination of survey results enriches the research by providing a deeper understanding of uncertainty, modelling complex scenarios, and enhancing predictive and decision-making capabilities. This approach strengthens the overall validity of the findings and demonstrates a comprehensive and meticulous handling of survey data.

In summary, integrating Monte Carlo analysis into the verification and validation phase of the data used in the SFD simulations enhances the robustness of the DSR process by providing a detailed and probabilistic assessment of the artefact. It allows for a thorough evaluation of the artefact's performance and reliability, ensuring that the design goals are achieved and that the artefact operates effectively across various scenarios.

7.3. Model Verification

Model verification focused on evaluating the conceptual models and CLDs in the thesis. These models illustrated the relationships between cognitive biases, stakeholder dynamics, and CE adoption processes. Verification included validating these models against empirical survey data and grounded theory methodologies to enhance their credibility and applicability, as specified in Chapter 3. The previous paragraphs focus on validation, ensuring the right data is used. This section focusses and verification, ensuring that the data is used correctly in the model (Petty, 2009:121-149).

Using CLDs and conceptual models provided visual representations that enhanced the understanding of complex interactions within the CE ecosystem. These graphical tools served as frameworks for conceptualising and analysing the interplay of variables, making them crucial for the verification process.

In the following paragraphs, the SFD simulation discussed in Chapters 3.3.3 and 3.3.5 is validated with a sensitivity analysis in Vensim using the Monte Carlo outcomes of the preceding sections in this chapter. See Appendix J – Vensim simulations for more details on the setup.

The simulation with Monte Carlo variables of the diagrams used in Chapters 4.7 and 6.4 is done in this section to verify the accuracy and robustness of the developed model. As discussed earlier, Monte Carlo simulations allow for exploring a wide range of possible outcomes by introducing random variations into the model's parameters,

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reflecting real-world uncertainty and variability. By incorporating these results into Vensim, a systems dynamics tool, it becomes possible to simulate the model's behaviour under different scenarios and parameter combinations, providing a deeper understanding of how cognitive biases influence decision-making processes over time. This process helps verify that the model behaves as expected across diverse situations, ensuring its reliability and predictive power. By comparing these simulated results with empirical data, the verification step ensures that the model can accurately represent real-world dynamics and that any discrepancies are identified and addressed for improved model reliability.

Table 32 presents a detailed mapping of the survey questions to key variables related to cognitive biases and sustainability used in the simulations in Figure 111. The table illustrates how each question aligns with the corresponding variable, providing insights into the role of cognitive biases in shaping perceptions and behaviours toward sustainability and the CE. The variables—Biases Stock, Opposed Cognitive Biases, Reference Sustainability Need Rate, and Reference Supporting Cognitive Biases—are crucial for understanding how different types of biases influence decision-making.

By connecting questions to these variables, this table enables a deeper analysis of the cognitive factors that affect sustainability practices and individual efforts to support environmentally friendly behaviours. This mapping will serve as a foundation for further analysis and model simulations to assess the impact of cognitive biases on adopting sustainability measures.

Table 32. SFD variables for verification with related Monte Carlo data references

Variable in SFD	Relating Monte Carlo questions
Biases stock	5 and 6
Opposed Cognitive Biases	3, 15 and 16
Reference sustainability need rate	1 and 4
Reference supporting cognitive biases	7, 8, 11 and 12

The same equations and variables were used for this simulation as for the simulation in Chapter 6.4. Table 33 details how the variable values differ and how they were calculated. See Figure 73 to Figure 110 above for the values used in the equations below, corresponding to the question number referenced in the discussion column.

Table 33. SFD variable discussion for simulation

Variable/simulation setting	Value (BaseCase)	Value (BaseCase) discussion	Value (HigherCap)	Value (LowerOpp)
Biases stock	114+136=250 (all the initial opposing biases)	Weibull Q5:114 (total for "poor" category) Q6:136 (total for "poor" category poor)	No change	125 (Half of base case)

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Opposed Cognitive Biases	(1000+4373+4099)/3=3158 (the total biases at play)	Weibull Q3:1000 (total biases) Normal Q15: (total biases) 2080+2262+32=4373 Q16: (total biases) 1879+2107+109+4=4099	6315 (Double the base case value)	No change
Reference sustainability need rate	1847/(5000+3153)=0.23 (focus and informed sustainability awareness)	Normal Q1: 5000 (Total "Yes") Q4: 3153/1847 (Total "Yes"/Total "No")	No change	No change
Reference supporting cognitive biases	1/((83+247/32+262)+(281+485/27)+(1628+2349/71+1)+(2048+2200/56))=0.96 (the ratio of the total biases to the total supportive bias count)	Weibull Q7: (83+247/32+262) Q11: (281+485/27) Normal: Q8: (1628+2349/71+1) Q12: (2048+2200/56)	No change	No change
Step increment	0.25	-	No change	No change
Initial value increment	0.00	-	No change	No change
Final value increment	100.0	-	No change	No change

The simulation results are shown in Figure 111.

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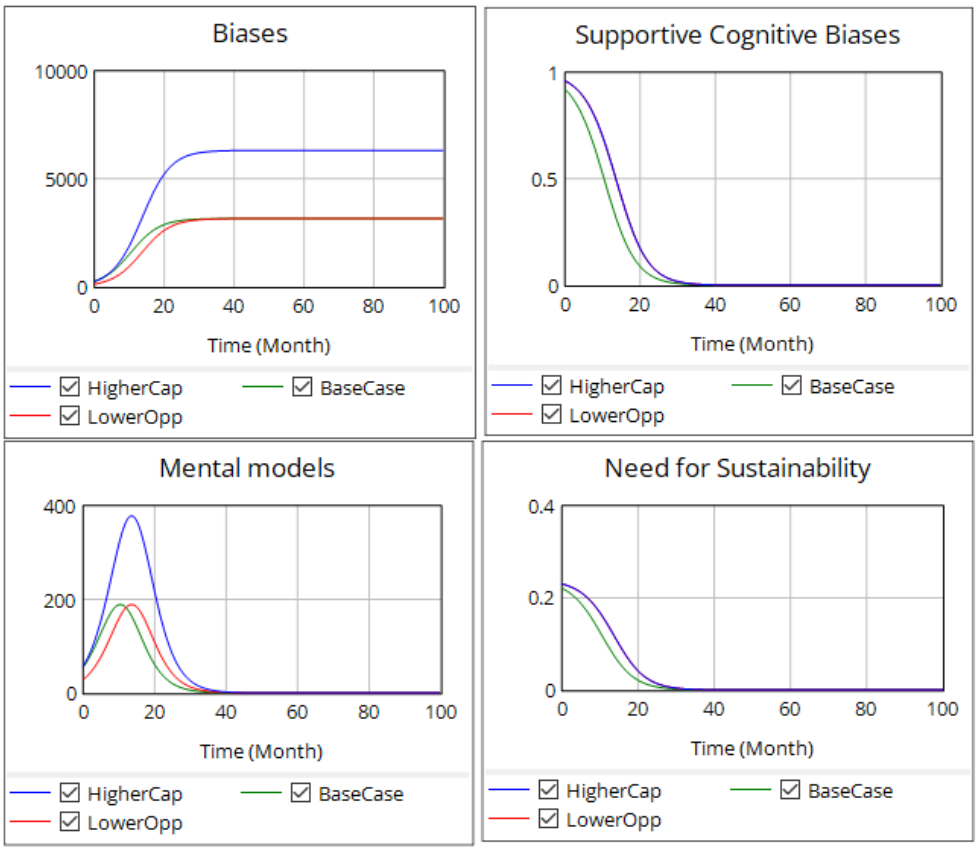

Figure 111. Vensim simulation graphs for SFD with Monte Carlo data

Biases (Stock) graph in Figure 112: The graph exhibits an S-shaped growth pattern typical of limits-to-growth models, with exponential growth in the early stages, followed by a shift at the inflexion point. The biases peak above 500 and plateau at 30 months, indicating that as opposing biases diminish, society's mental models gradually shift towards a more sustainable and holistic outlook. However, when the capacity for opposing biases increases, as seen in the blue line, the system struggles to recover to its original baseline. This suggests that supportive biases cannot fully restore the system once opposing biases dominate, preventing a return to a sustainable state.

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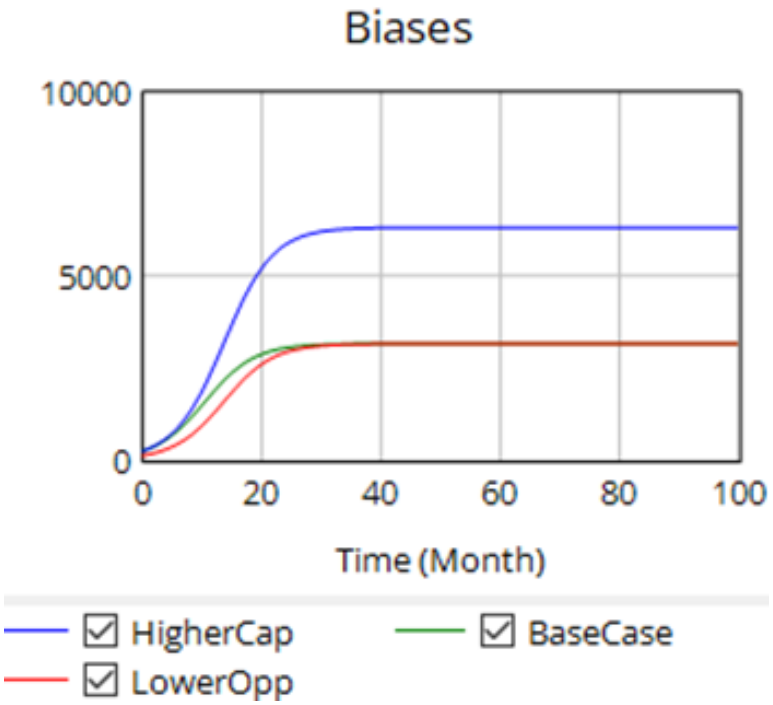

Figure 112. Vensim simulation graphs for SFD with Monte Carlo data - Biases

Supportive Cognitive Biases graph in Figure 113: This graph demonstrates that supporting biases peak when the overall stock of biases is at its lowest, aligning with the earlier explanation of mental models. Supportive biases plateau before 40 months, indicating a rapid peak and decline as overall biases increase, and the influence of supporting biases diminishes due to residual opposing biases. The red and blue lines coincide, reflecting the strong relationship between these changing variables and opposing biases. Over time, the availability ratio of supportive biases, ranging from 0 to 1, decreases as opposing biases grow, limiting the system's ability to maintain strong supportive influences.

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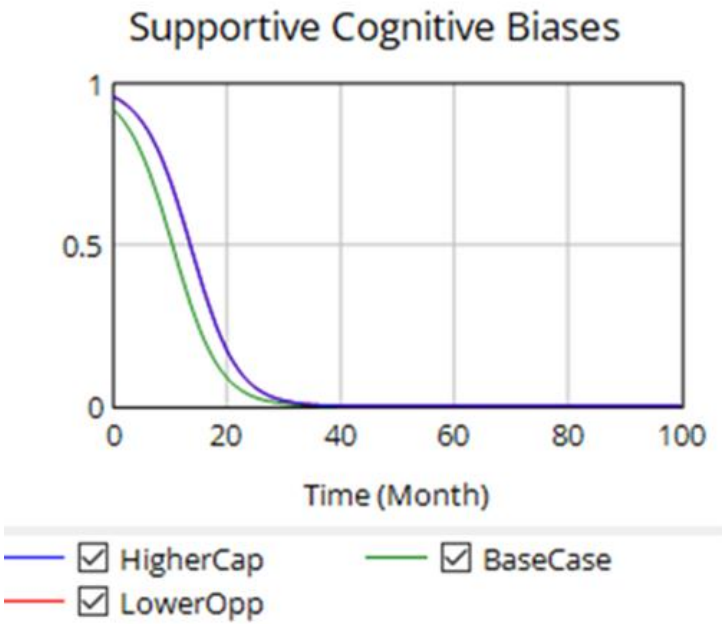

Figure 113. Vensim simulation graphs for SFD with Monte Carlo data - Supportive Cognitive Biases

Need for Sustainability graph in Figure 114: This graph shows the need for sustainability influenced by biases. The need peaks just above 0.2 and then declines to 0 by 30 months. This decline corresponds with the diminishing supportive biases. The system reaches a zero point when opposing biases surpass supporting biases, making further growth unattainable. The blue line, indicating a higher capacity for opposing biases, and the red line, representing lower initial opposing biases, coincide, showing that the perceived need for sustainability takes longer to decline as opposing biases dominate.

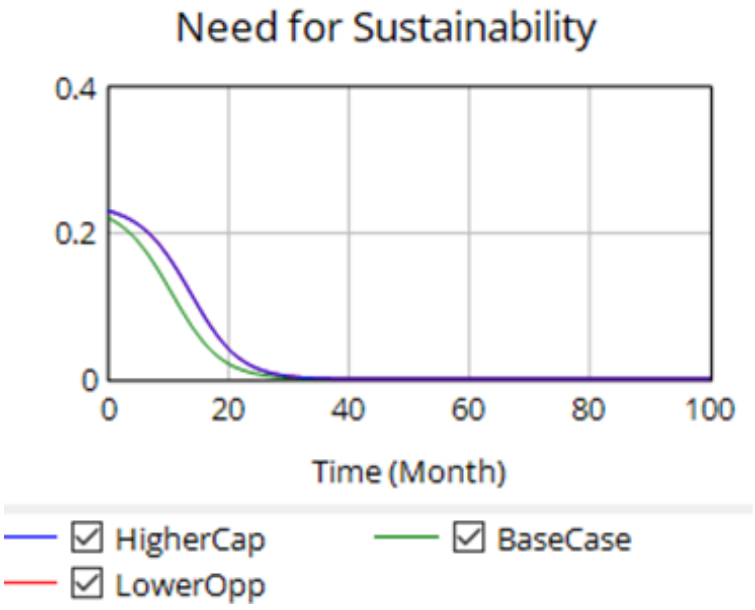

Figure 114. Vensim simulation graphs for SFD with Monte Carlo data - Need for Sustainability

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Mental Models graph in Figure 115: The final graph illustrates the evolution of society's mental models, following a characteristic bell-shaped curve. The mental models peak at almost 400 between 10 and 15 months, indicating rapid growth followed by a decline. As biases cease to be the primary influence, mental models are driven by the system's net flow of perceived needs. The green and red line scenarios are close, indicating that with a low capacity for biases and fewer opposing biases, mental models do not significantly influence sustainability outcomes. However, when opposing biases are high, mental models play a more direct role in shaping sustainability.

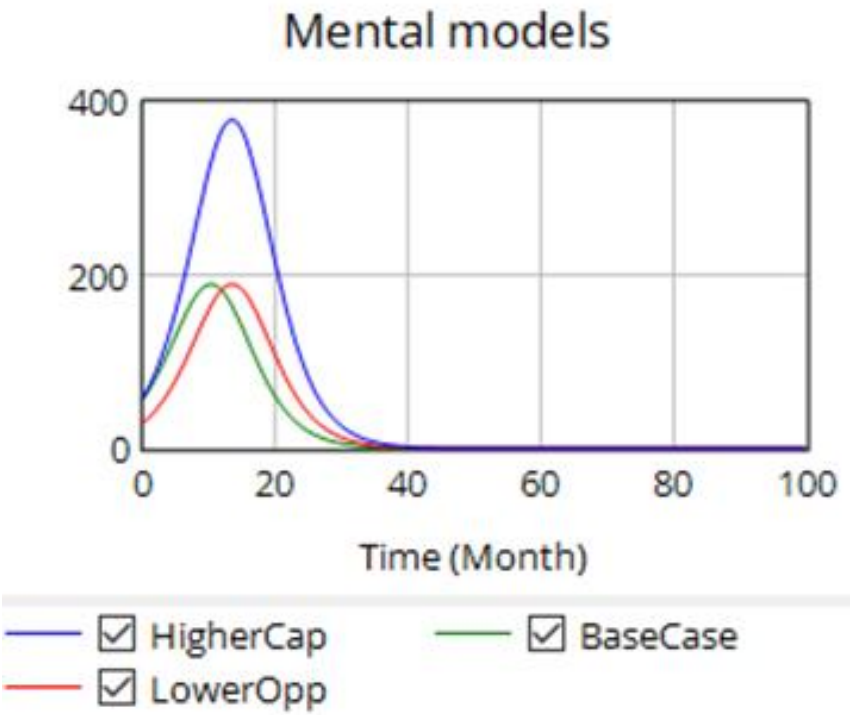

Figure 115. Vensim simulation graphs for SFD with Monte Carlo data - Mental Models

See Chapter 8.2 for a comparison between the Survey Vensim simulations and the Monte Carlo Sensitivity analysis. The Vensim software can be utilised in future studies to simulate more complex systems through its Monte Carlo sensitivity analysis feature, allowing the researchers to explore the impact of variable uncertainty and conduct risk analysis for these models. Additionally, Vensim's powerful simulation capabilities enable the modelling of dynamic systems over time, can help to evaluate different scenarios and optimise decision-making processes in various fields.

7.4. Conclusion

The validation and verification processes underscored the importance of adopting a ST approach to understand the interconnectedness of factors influencing CE adoption. CE adoption relates to the perceived need for sustainability. By comprehensively analysing data and verifying models, the research highlighted the multifaceted nature

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of cognitive biases and their impact on decision-making processes. This approach validated the theoretical frameworks.

The validation and verification steps are not merely procedural but are research activities that evaluate the model's effectiveness, contributing to its overall research contribution. In future research it may now be possible to use these distributions calculated using Monte Carlo techniques in Vensim to do Monte Carlo uncertainty simulations of the SD models in Vensim directly and compare the outcomes.

The chapter concludes that the survey data and the SFD model are reliable for use in the final results chapter. It critically analyses the design and evaluation processes, highlighting strengths and areas for enhancement.

The methodologies and validation processes presented in this section not only strengthen the empirical foundation of the research but also provide valuable contributions to theory, practice, and policy in CE adoption. The validation of cognitive biases through thematic coding, Monte Carlo simulations, and statistical distribution fitting enhances the theoretical understanding of how biases shape sustainable decision-making. By employing both deductive and inductive coding, the study identifies emerging themes that expand current literature, particularly in how cognitive biases influence stakeholder engagement with sustainability. The transition from Weibull to Normal distribution analysis further refines the quantification of biases, offering a methodological advancement in modelling decision-making uncertainty within CE frameworks. These theoretical contributions lay the groundwork for a systematic approach to studying cognitive biases in sustainability and will be further synthesized in Chapter 8 as part of the research’s broader implications.

Beyond theory, the validation methods offer practical insights that can enhance decision-making models for policymakers, businesses, and sustainability practitioners. The Monte Carlo simulations illustrate how bias-driven behaviours evolve over time, providing a predictive tool to assess when opposing biases might hinder sustainability adoption. This insight enables policymakers to pre-emptively design interventions that counteract cognitive distortions, such as framing sustainability incentives in ways that minimize loss aversion or confirmation bias. The results also inform corporate sustainability strategies, helping organizations implement evidence-based decision-making frameworks that account for cognitive biases in employee and consumer behaviours. Furthermore, by validating the impact of biases on CE adoption, this research provides policy recommendations that address systemic barriers to sustainability. These include the need for bias-aware policy designs, improved risk communication strategies, and enhanced regulatory mechanisms to sustain long-term engagement in CE initiatives. These findings will be expanded upon in Chapter 8.

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8. Results discussion

Chapter 8 discusses the results, providing explanations and insights for further model use. It also addresses the limitations and assumptions of the research. This section fits into the DSR framework of the thesis, as shown in Figure 116.

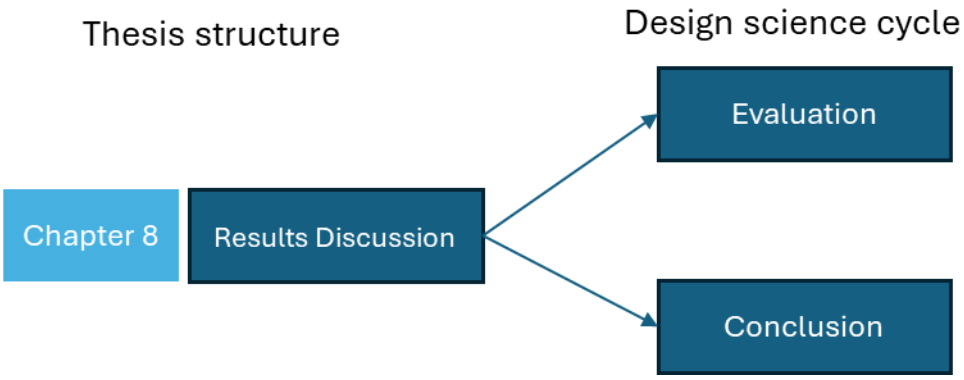

Figure 116. Design Science Research Framework - Chapter 8

Picture a complex ecosystem where every species is interconnected. If a single species' behaviour is misunderstood, it can throw the entire system out of balance. In this chapter, the research reflects on how integrating SE with cognitive biases throughout the thesis has provided new insights into the sustainability ecosystem of the CE. Just as understanding each species' role is crucial for maintaining ecological balance, the research contributes to a deeper understanding of guiding stakeholders toward sustainable practices by considering both technical and human factors. The discussion emphasises the broader implications of the findings for engineering management and sustainability.

The validated CLDs from Sections 4.5 and 6.4.1 were merged, and the SFD from Section 6.4.1 was modified with the variables from the validated CLD in 4.5. A qualitative analysis was completed with additional survey data to validate all the connections in the new CLD and to run a few simulations on the new SFD, as shown in Chapters 3, 6 and 7.

Figure 117 represents the culmination of this research, showcasing a final combined and validated CLD that integrates multiple layers of cognitive biases within the CE framework. The novelty of this figure lies in its comprehensive synthesis of various bias influences, drawing from numerous sub-models to create a holistic and dynamic representation of stakeholder decision-making processes. Unlike traditional CLDs that often focus on linear relationships or isolated feedback loops, this diagram captures the complexity of cognitive interactions, providing a nuanced understanding of how biases interact and compound over time. The contribution of this CLD is significant, as it offers a validated tool that can be used by policymakers, systems engineers, and

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sustainability practitioners to identify leverage points where interventions can most effectively mitigate negative bias impacts, thereby enhancing sustainability outcomes (Challender, 2000:S78-S80). The CLD has been validated through grounded theory, as discussed in Chapter 3.

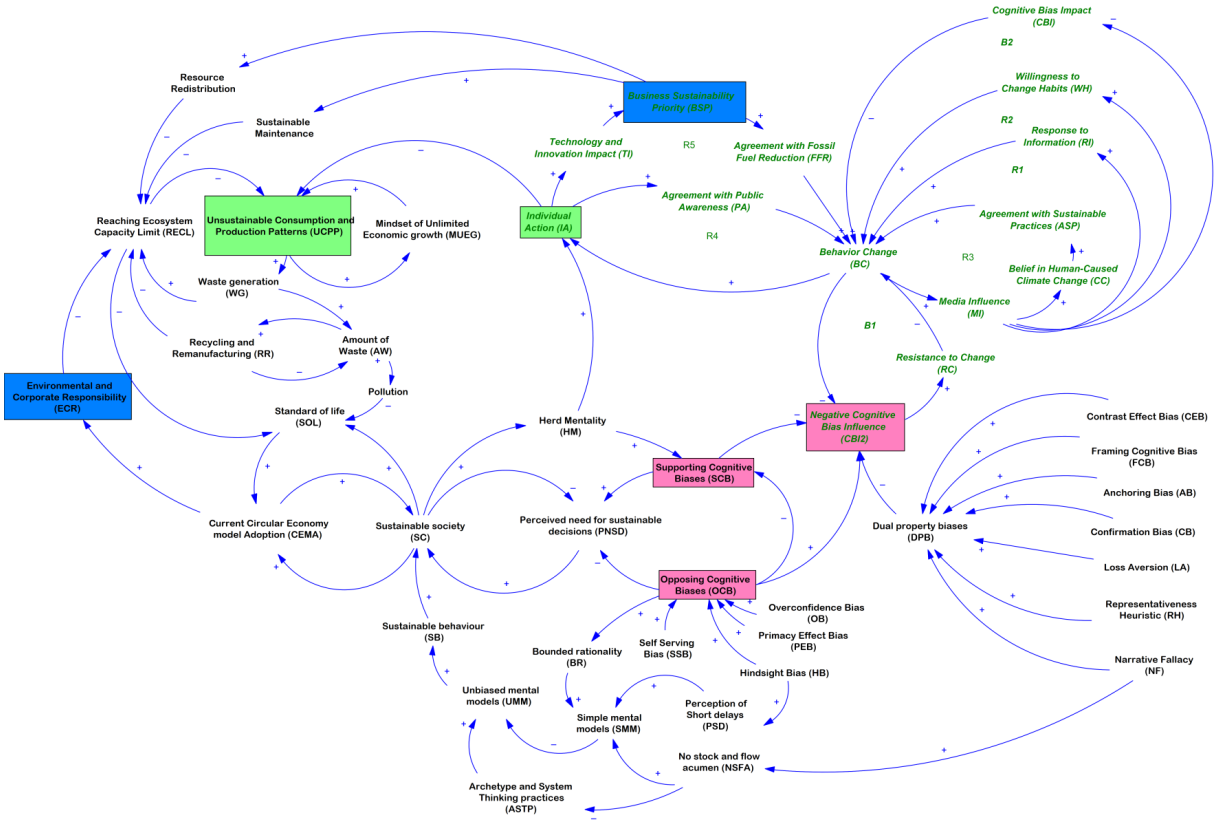

Figure 117. Final combined and validated CLD

Figure 118 presents the final combined and validated SFD, an innovative tool that extends traditional SFD methodologies by incorporating cognitive bias variables into the flow of resources and decisions within the CE. The model development is discussed in Chapter 3.3, and the validation is discussed in Chapter 7. This figure's novelty is evident in its ability to visually and quantitatively model how biases influence resource flows, delays, and accumulations within a CE system, offering a more accurate reflection of real-world decision-making complexities. The diagram's contribution is particularly valuable for its ability to simulate different scenarios, allowing stakeholders to explore the effects of various biases on sustainability metrics. By integrating cognitive biases into the stock and flow analysis, this SFD provides an approach that enhances the predictive power of sustainability models, offering a critical resource for improving decision-making processes and achieving long-term CE goals. See Section 3.3.7 for the full discussion on model development.

The SFD presented in Figure 118 is a simplified, shortened version that does not incorporate all the elements of the more comprehensive CLD shown in Figure 117 or previous models. This reduction is intentionally aimed at focusing on the most critical

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stocks and flows directly related to the influence of cognitive biases on decision-making within the CE. While Figure 117 and earlier models contain a broader scope of variables and feedback loops that detail the complex interrelationships among various stakeholders, resources, and environmental factors, Figure 118 narrows the scope to ensure clarity and usability for specific simulation purposes. This simplification is particularly useful for running simulations, as it isolates key variables directly linked to biased decision-making processes, enabling more precise analysis and insights without overwhelming the model with too many interconnected elements (Lane and Rouwette, 2022). By concentrating on core components, Figure 118 offers a streamlined view that retains the essence of the system's dynamics while making the analysis more manageable and focused on the research objectives of this thesis. Further research can be conducted by extending the SFDs based on these simulation results.

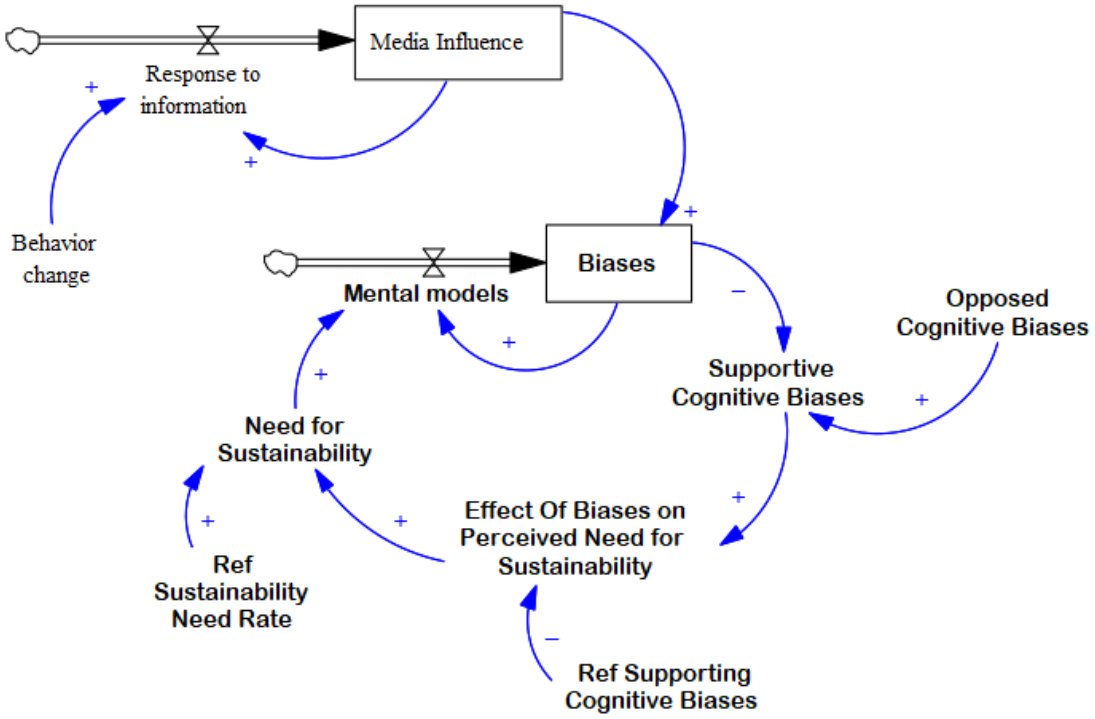

Figure 118. Final combined and validated SFD

The model development for this section is discussed in Chapter 3.3.7, together with the simulation variables and equations. A portion of this SFD was validated in Chapter 7.

8.1. Research results

Figure 118 was used to model and simulate the dynamics of cognitive biases in sustainable decision-making within the CE. This section details the key variables used in the SFD and the simulations' outcomes. The SFD model integrates several critical

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variables to represent the complex interactions within the CE system influenced by cognitive biases:

- Stocks (State Variables):
  - Awareness of cognitive biases: This stock measures the extent to which stakeholders are aware of cognitive biases affecting their decision-making.
  - Media influence on sustainability: This stock captures the overall impact of media (both positive and negative) on public perception and behaviour towards sustainability.

- Flows (Rates of Change):
  - Rate of adoption of sustainable practices: The rate at which sustainable practices are being adopted over time, influenced by awareness levels and media influence.
  - Change in awareness: The rate at which awareness of cognitive biases increases or decreases, affected by media literacy initiatives.
  - Media influence dynamics: The flow representing changes in media influence, modulated by the type and frequency of sustainability-related media coverage.

- Auxiliary Variables:
  - Leverage points: Identified points where interventions can be applied to effect change in the system.

In the graphs shown in Figure 119, the horizontal axis is labelled "Time [months]," and the vertical axis consistently uses units of measurement such as [number/ratio of].

Months provide an appropriate level of granularity for capturing SD without being overly detailed or overwhelming. This time frame allows for meaningful insights while keeping the scope manageable. Observing changes within the system over months is realistic, as decision-making processes and behavioural shifts often occur over weeks or months rather than days.

It is important to consider the nature of biases and their influence on stakeholder behaviour. Cognitive biases often manifest subtly and gradually, with their effects becoming more noticeable over extended periods. Decision-making processes in the CE are rarely instantaneous and are influenced by a multitude of factors that develop and evolve over time, such as stakeholder interactions, resource allocation, and sustainability initiatives. By using months as the time scale, the model is able to capture these gradual shifts, allowing for the observation of longer-term patterns in biased decisions and behavioural adjustments. This level of granularity strikes a balance between providing sufficient detail to understand the systemic effects of biases while

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avoiding the noise that might result from using shorter daily intervals. The monthly time frame facilitates a clearer identification of trends, inflexion points, and systemic feedback loops within the decision-making process, ultimately offering a more robust analysis of how cognitive biases affect sustainability outcomes. The monthly unit was not part of the survey and was not validated, but future research can do time lapse surveys with bias recognition to validate the unit.

Figure 119 illustrates the simulation outputs from Vensim of the final SFD, showcasing the practical application of the model developed in this research. See Appendix J – Vensim simulations. The novelty of this figure is in its demonstration of how cognitive biases can be quantitatively simulated within a systems dynamic framework, providing empirical evidence of their impact on sustainability outcomes within the CE, as seen in Table 34.

Unlike conventional simulations that may overlook the human factors in decision-making, this figure offers an approach to understanding how biases influence system behaviours over time. Other authors that address human effects in simulations are Van Dyk and Pretorius (2014:71-84). The value of these simulations lies in their ability to predict potential system responses to various interventions, offering stakeholders a powerful tool to forecast the effectiveness of debiasing strategies.

By providing actionable insights into how biases affect sustainability, this figure substantially contributes to theory and practice, reinforcing the importance of integrating human cognition into SE models (Bolis et al., 2017:310-322).

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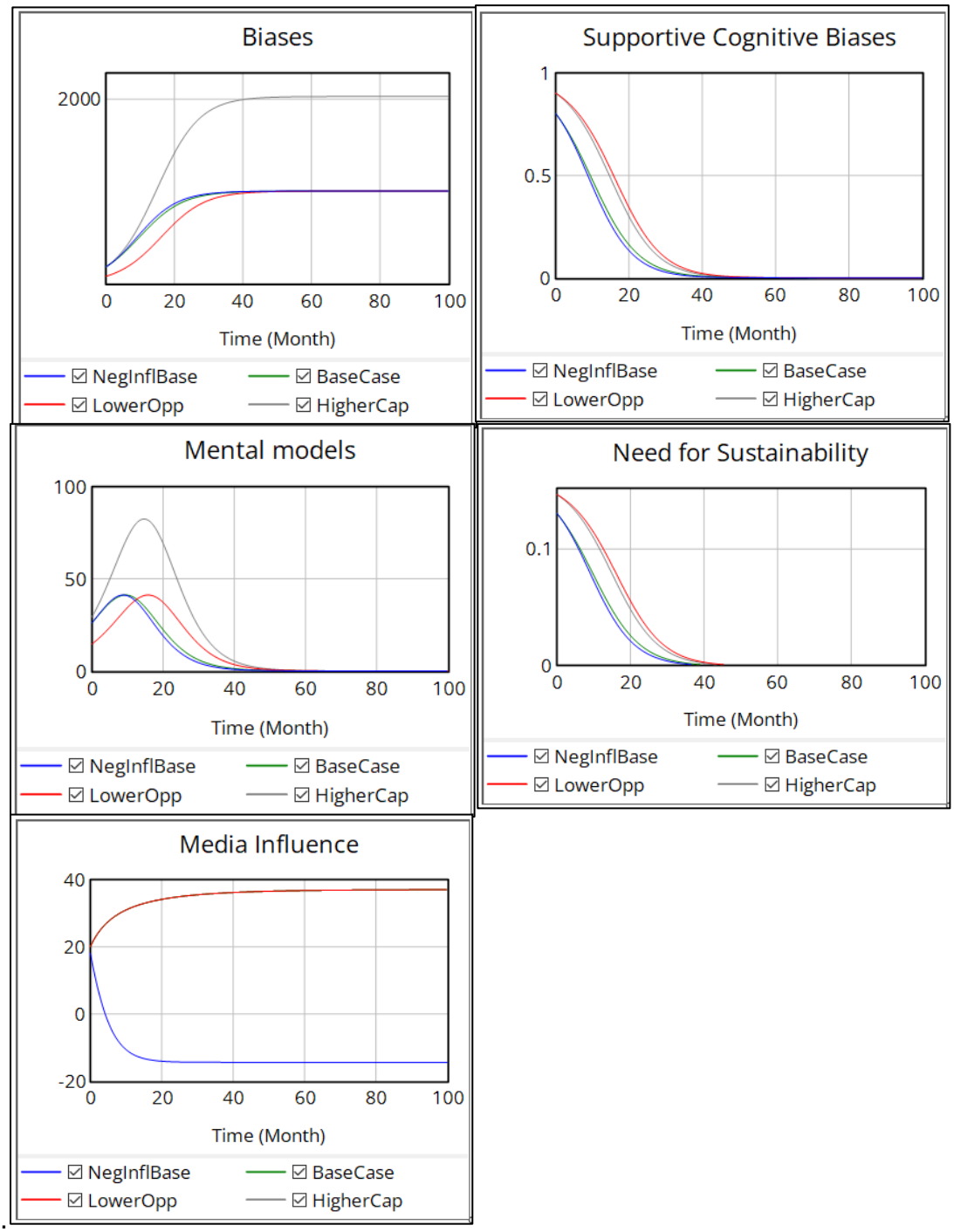

Figure 119. Simulations of final SFD

The SFD simulations provided insights into how different variables interact over time and the potential outcomes of various intervention strategies. See Chapter 8.2 for the detailed discussions for each graph. Key findings from the simulations include:

- Baseline Scenario (green lines in Figure 119):
  - Without interventions, adopting sustainable practices remains slow due to the strong influence of cognitive biases and negative media influence.
  - Awareness of cognitive biases increases gradually but cannot significantly alter decision-making behaviours.

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- Positive Media Influence Scenario:
  - Introducing consistent positive media coverage significantly boosts the adoption rate of sustainable practices.
  - Awareness of cognitive biases increases more rapidly as positive media reinforces the importance of addressing these biases.
  - The combined effect leads to a higher adoption of sustainable practices over time.

This section explored the influence of cognitive biases on decision-making within the CE through BSD and empirical survey data, as discussed in Chapters 3, 4, 5 and 6. Key findings include:

- Cognitive biases significantly shape perceptions and decisions related to sustainability.
- The conceptual CLD was validated and integrated with another CLD to form a comprehensive model, which was then combined with an existing SFD.
- Survey results revealed that confirmation and status quo bias hinder the adoption of sustainable practices by influencing how individuals and organisations perceive risks and rewards.
- Media influence plays a critical role in shaping sustainability attitudes. Positive media influence encourages sustainable behaviour changes, while negative media influence reinforces resistance to change.
- The study identified specific leverage points for interventions, such as increasing awareness of cognitive biases and promoting media literacy, to enhance sustainable decision-making.

8.2. Discussion

Table 34 presents a detailed overview of the final simulation results, synthesising the data gathered through various modelling techniques and empirical analysis conducted throughout this research. The table is designed to illustrate key outcomes of the simulations, particularly focusing on the integration of cognitive bias variables into the CE framework. These results provide insight into how biases affect decision-making at different stages within the CE, highlighting critical leverage points for enhancing sustainability practices.

As discussed in earlier chapters, particularly Chapter 6 on data analysis and Chapter 7 on validation, these simulations were instrumental in verifying the effectiveness of the proposed model. Table 34 serves to summarise these findings and further emphasise the novel contributions of this research toward debiasing decision-making processes in complex systems. Each separate graph is first presented and then discussed in Table 34.

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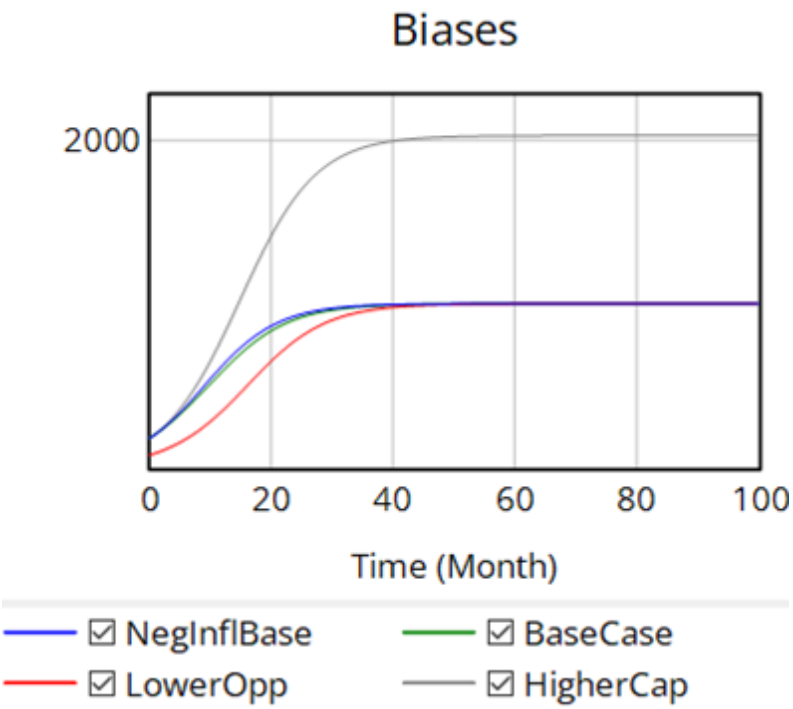

Figure 120. Simulations of final SFD - Biases

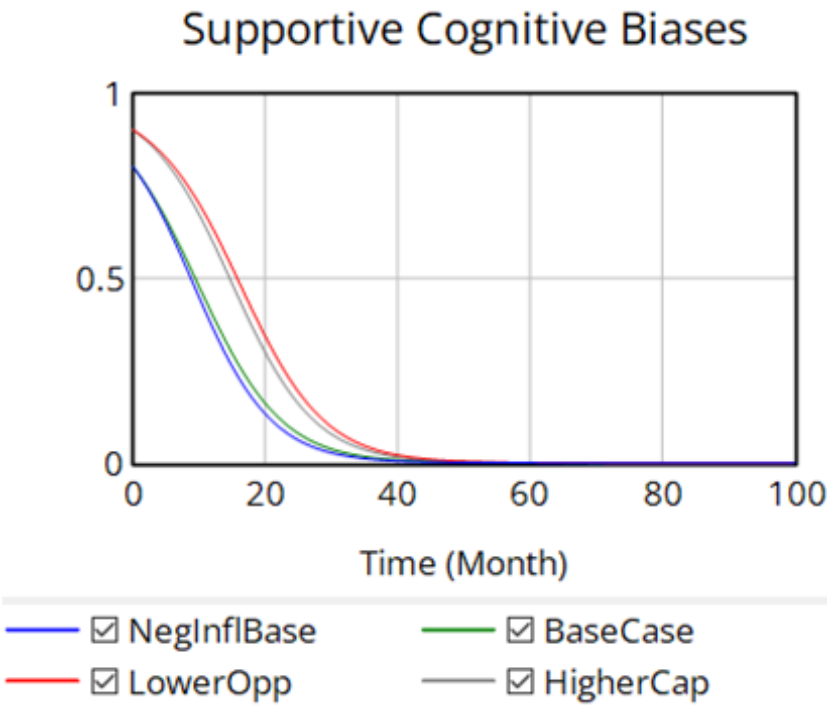

Figure 121. Simulations of final SFD - Supportive Cognitive Biases

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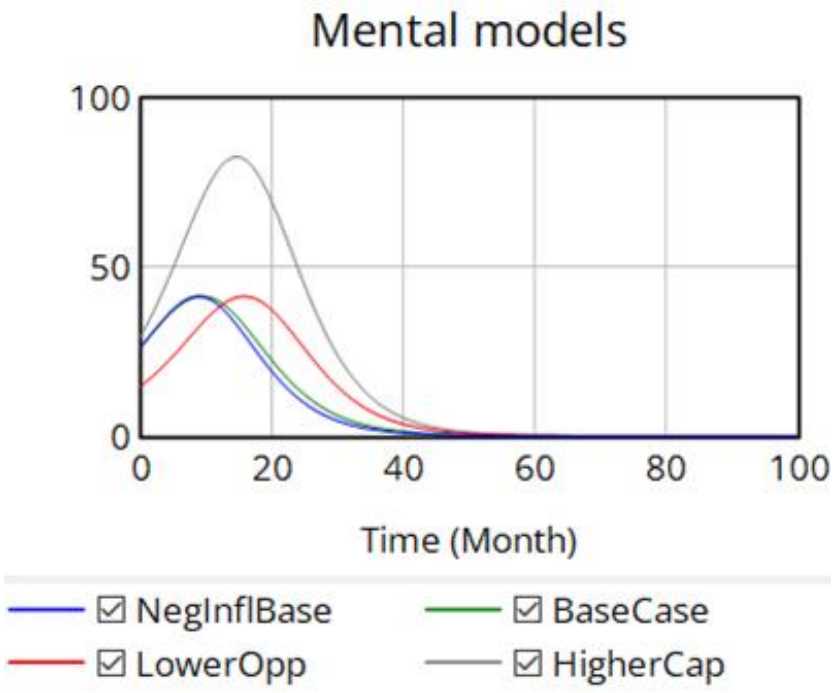

Figure 122. Simulations of final SFD - Mental Models

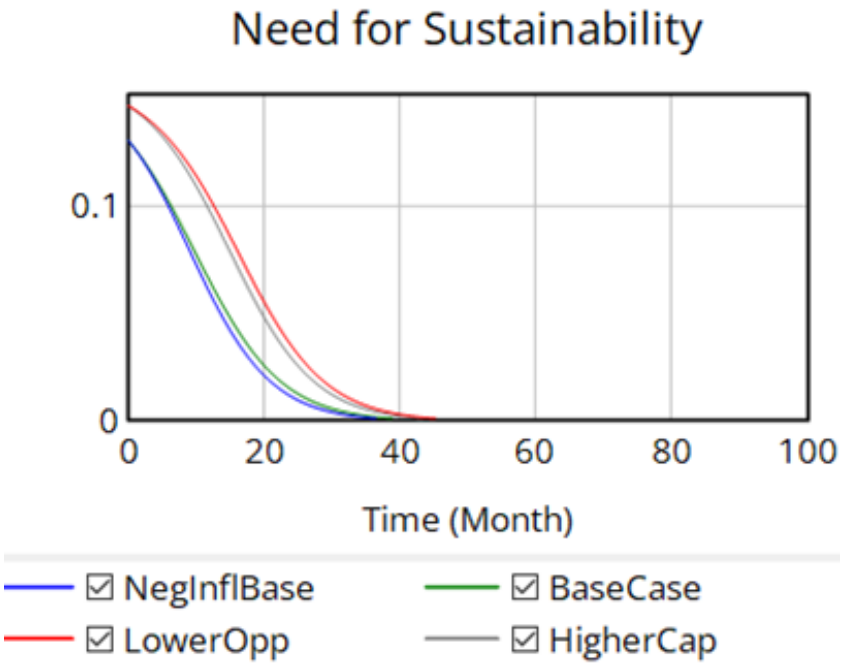

Figure 123. Simulations of final SFD - Need for sustainability

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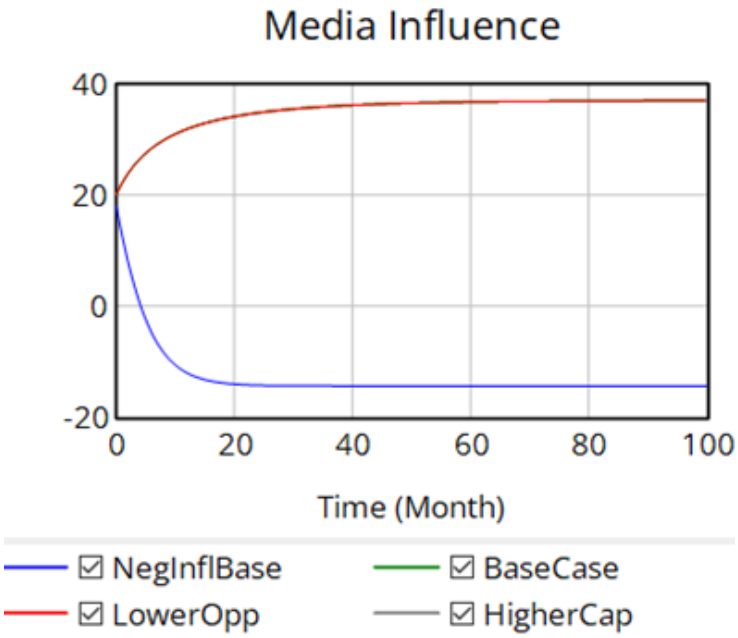

Figure 124. Simulations of final SFD - Media Influence

Each graph from Figure 120 to Figure 124 os discussed below.

Table 34. Results of final simulation – discussion

Graph	Base case	Lower opposing case	Higher capacity case	Negative influence case
Biases (Figure 120)	The Biases simulation graph exhibits an upward S-shaped growth, illustrating how biases evolve under various scenarios. In the base case, biases grow to a median level within a specified period, showcasing a typical S-shaped or logistic growth pattern where biases increase rapidly and then plateau as the system nears its carrying capacity.	In the LowerOpp scenario, the growth follows a lower S-shape and reaches the median later than the base case, indicating that reduced opposing biases slow the growth rate. This suggests that biases take longer to develop with fewer opposing forces fully.	The HigherCap scenario shows biases reaching their maximum simultaneously as the base case but achieving a higher overall level due to increased capacity for biases. This implies that the system can support more biases, allowing for more pronounced growth without significantly altering the timing of peak biases.	In the NegInflBase scenario, which incorporates the negative influence of behavioural changes and responses to information, biases surpass the base case. This indicates that these negative influences slightly accelerate bias growth, possibly by reinforcing certain biases or weakening opposing forces.
Supportive cognitive biases (Figure 121)	The Supportive Cognitive Biases simulation graph displays a downward S-shaped trend, showing how supportive biases	In the LowerOpp scenario, the S-shape is the highest, with supportive biases reaching zero more	The HigherCap scenario shows a decline just below that of the LowerOpp case, indicating that a higher capacity for biases slightly	In the NegInflBase scenario, the decline in supportive biases is just below the base case, implying that negative influences from behaviour changes

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	diminish over time under various scenarios. In the base case, supportive cognitive biases quickly drop to zero within a shorter period, indicating a rapid decline likely due to opposing biases or other factors that counteract supportive biases.	slowly. This suggests that with fewer opposing biases, supportive biases persist longer and decrease more gradually.	speeds up the reduction of supportive biases. Although the capacity for biases increases, the timing of the decrease remains similar to LowerOpp, reflecting a similar dynamic in how biases influence supportive cognitive biases.	and responses to information accelerate the reduction of supportive biases. This suggests that these negative influences lead to a quicker decline in supportive biases compared to the base case.
Mental models (Figure 122)	The Mental Models simulation graph exhibits an upward bell curve, representing the evolution of mental models over time across various scenarios. In the base case, mental models peak at a median level before declining within a shorter timeframe. This pattern suggests that as biases and the need for sustainability increase, mental models also rise, but as the system advances and biases decrease, mental models begin to decline.	In the LowerOpp scenario, the peak occurs later, and mental models reach zero last, similar to the HigherCap scenario. This delayed peak and extended duration imply that mental models persist at higher levels with fewer opposing biases for a more extended period.	The HigherCap scenario shows the highest peak between the base case and LowerOpp. This indicates that a higher capacity for biases allows mental models to reach higher levels quickly, but the duration remains similar to LowerOpp.	The NegInflBase scenario displays a peak similar to the base case, but the decline is slightly steeper. This suggests that the negative influence of behaviour changes and responses to information causes a faster decline in mental models compared to the base case.
Need for sustainability (Figure 123)	The Need for Sustainability simulation graph shows a downward S-shaped trend, illustrating how the perceived need for sustainability changes over time across different scenarios. In the base case, the need for sustainability drops quickly to zero within a shorter period. This rapid decline might indicate that	In the LowerOpp scenario, the S-shaped curve is the highest and takes the longest to reach zero, suggesting that the perceived need for sustainability declines more slowly with fewer opposing biases. This may be because individuals	The HigherCap scenario shows a curve just below LowerOpp, with a similar decline pattern but reaching zero slightly sooner. A higher capacity for biases may mean that, although there are more biases in the system, the perceived need for sustainability decreases, like in the LowerOpp scenario.	The NegInflBase scenario displays a decline just below the base case, indicating that negative influences from behaviour changes and responses to information accelerate the reduction of the perceived need for sustainability. This might be due to changes in individual behaviours or attitudes that lead to a quicker decrease

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	individuals perceive less urgency for sustainability as the system evolves, likely due to decreasing biases and a shift towards more sustainable practices, known as the 'status quo' effect.	continue to see a need for sustainability over a more extended period without opposing solid biases.		in the perceived necessity of sustainability.
Media influence (Figure 124)	The Media Influence simulation graph features two exponential growth curves, showing how media influence evolves in various scenarios. The curves in the base case, HigherCap, and LowerOpp scenarios align with a positive exponential growth trend that gradually increases. This pattern suggests that positive media influence consistently rises in these scenarios as biases and other system factors change. The steady growth implies that media influence shapes perceptions and behaviours over time, mainly as biases develop.			In contrast, the NegInflBase scenario displays a negative exponential growth curve with a sharper decline. This indicates that behaviour changes and responses to information lead to a faster reduction in media influence. It underscores how negative influences, such as conflicting information or behaviours opposing sustainable practices, can swiftly diminish media's impact on perceptions and decision-making.

The discussion below delves into the implications of the research findings:

- Impact of cognitive biases: The study highlights how cognitive biases distort decision-making processes in the CE, leading to suboptimal resource utilisation and missed opportunities for innovation. Addressing these biases is crucial for promoting sustainable production and consumption patterns (Singh and Giacosa, 2019:921-937).
- Role of media influence: Media has a dual role in promoting or hindering sustainability. Positive media coverage can leverage the effects of cognitive biases by presenting sustainability in a favourable light, whereas negative media can exacerbate resistance to change (Ivanaj, 2024:3).
- Interventions and strategies: Effective strategies to counteract cognitive biases include educational campaigns to raise awareness, initiatives to enhance media literacy, and creating environments that support sustainable practices. These interventions can help stakeholders make more informed decisions, fostering a culture of sustainability.
- Stakeholder engagement: Engaging various stakeholders, from policymakers to consumers, is vital. Understanding the cognitive biases that affect different groups

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can help tailor interventions that address specific needs and barriers to sustainable practices.

If the simulations and graphs generated during this research were non-linear, it would signify that the relationships between variables within the CE framework and cognitive biases are more complex than initially anticipated. Non-linear patterns often suggest the presence of feedback loops, threshold effects, or emergent behaviours that are not evident in linear models. For instance, a slight change in stakeholder behaviour influenced by cognitive biases could lead to disproportionately large impacts on sustainability outcomes, indicating that certain biases might have tipping point effects that either accelerate or decelerate progress toward sustainability goals.

The non-linear behaviour in the simulations could stem from several factors intrinsic to complex systems. One primary reason is the interaction between multiple cognitive biases, where the combined effect of biases like confirmation bias (where individuals favour information that confirms their preconceptions) and availability heuristics (where people judge the probability of events based on how easily examples come to mind) could amplify or mitigate their individual impacts.
For instance, confirmation bias might cause an individual to continually seek out information that supports their initial beliefs, while the availability heuristic might make them more likely to recall and use this information, reinforcing the bias. This synergistic effect can lead to a rapid escalation or suppression of certain behaviours that would not be as pronounced if each bias operated in isolation. Additionally, the inherent dynamics of the CE, such as resource depletion, regenerative cycles, and stakeholder interactions, are often non-linear, reflecting real-world complexities where outcomes are not directly proportional to inputs. These dynamics involve delayed effects, where the impact of a decision becomes evident only after a certain threshold is crossed, further complicating predictive modelling.

It is recommended that advanced SD techniques capable of capturing these complexities be employed in future studies to manage and effectively utilise non-linear models. Sensitivity analysis should be conducted to identify critical leverage points within the system—specific variables or parameters where small changes could lead to significant outcomes. Furthermore, incorporating adaptive strategies into the decision-making framework can allow stakeholders to respond more flexibly to unexpected changes, ensuring that sustainability goals are met despite unpredictable system behaviour. Techniques such as Monte Carlo simulations or agent-based modelling could also help understand the possible outcomes in non-linear systems.

Sustainability and the CE are intrinsically linked, with CE embodying many sustainability principles. CE aims to minimise waste, enhance resource efficiency, and create closed-loop systems where products and materials are continuously reused and

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recycled. This aligns with sustainability goals by ensuring that current practices do not deplete resources or harm future generations' ability to meet their needs. CE addresses environmental sustainability and promotes economic viability through resource optimisation and innovative business models, and can positively impact social sustainability by fostering equitable and sustainable communities (Korhonen et al., 2018:544-552). Increasingly, policies and regulations emphasise the need for sustainability, driving businesses to adopt CE practices (Prieto-Sandoval et al., 2018:605-615). Incorporating a variable for "need for sustainability" in the model can thus capture the growing demand for sustainable practices and assess how this need influences the effectiveness of CE strategies, resource management, and overall environmental and economic outcomes.

If the non-linear characteristics of the model are appropriately accounted for, the outcomes can provide a more accurate and nuanced understanding of the CE's dynamics. Stakeholders could anticipate potential risks and opportunities better, leading to more resilient and robust sustainability strategies. Additionally, recognising and addressing the non-linear interactions between cognitive biases and decision-making processes could lead to more targeted interventions, enhancing the overall effectiveness of sustainability initiatives. Ultimately, embracing the complexity revealed by non-linear simulations could drive more innovative solutions, contributing to the long-term success of the CE. This is not shown in this thesis; the decision was made to focus on linear or simplified models to maintain clarity in the analysis and ensure that the results remained closely aligned with the survey data and the specific research objectives. The linear approach allowed for more manageable simulations that could be effectively validated through Monte Carlo analysis and comparison with real-world data.

Table 35 presents a comparative analysis of the different simulation methods used to explore the evolution of cognitive biases, supportive biases, mental models, and sustainability perceptions in the system. The table contrasts the outcomes from the Conceptual SFD Vensim simulation with survey data from Chapter 6.4, the Monte Carlo simulation results from Chapter 7.3, and the final SFD Vensim simulation incorporating survey data from Chapter 8.1. Each column illustrates how biases and system variables evolve under different scenarios and how the model responds to varying levels of complexity and uncertainty. By integrating real-world survey data and conducting Monte Carlo simulations, the analysis provides a deeper understanding of the potential pathways and outcomes in decision-making processes influenced by cognitive biases. The results offer insights into how different system factors interact to either accelerate or slow down the shift toward sustainability, depending on the assumptions made and the dynamics modelled in each simulation.

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Table 35. Vensim simulation comparisons between Conceptual, Monte Carlo and final SFD

Graph	Conceptual SFD Vensim simulation with Survey data from Chapter 6.4	Monte Carlo simulation from Chapter 7.3	Merged SFD Vensim simulation with Survey data from Chapter 8.1
Biases	Exhibits an upward S-shaped growth as biases develop over time. Peaks and plateaus indicate the system's carrying capacity for biases. (Figure 66)	Demonstrates a range of possible bias evolution paths based on different scenarios, highlighting uncertainty. (Figure 112)	Confirms bias development over time, with similar peaks and plateaus compared to conceptual simulation. (Figure 120)
Supportive cognitive biases	Depicts a downward S-shaped trend, showing how supportive biases diminish as opposing biases grow. (Figure 67)	Simulations reveal different timings and rates for the decline of supportive biases. Some scenarios suggest prolonged persistence, while others show a rapid decline. (Figure 113)	Similar to the conceptual simulation, but with slight differences in the timing of the decline based on media influence, empirical feedback loops were observed. (Figure 121)
Mental models	Follows a bell curve, with mental models rising to a peak and then declining as biases decrease and the need for sustainability diminishes. (Figure 69)	Monte Carlo results demonstrate different peak timings for mental models, reflecting varying assumptions about bias influence. (Figure 115)	Empirical data suggests an earlier peak and a faster decline than observed in the conceptual simulation, aligning with real-world observations of media influences. (Figure 122)
Need for sustainability	Shows a rapid decline in the perceived need for sustainability after an initial peak, following a downward S-shaped trend. (Figure 68)	Varies depending on the bias and opposing bias interaction, with different rates of sustainability decline modelled. (Figure 114)	Supports a faster decline in the perceived need for sustainability, matching real-world decision-making processes and the quicker erosion of sustainability urgency, especially for negative media influence. (Figure 123)
Media influence	-	-	Shows a more nuanced effect of media influence, with the timing and strength of growth dependent on specific survey data responses. Biases are directly influenced by either positive or negative media. (Figure 124)

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If the underlying paradigm of the CE were to change, it would have profound implications for the systems and models developed in this research. A paradigm shift could involve a fundamental rethinking of managing resources, possibly moving from the current focus on resource efficiency and recycling to more radical approaches such as regenerative design, biomimicry, or even de-growth strategies prioritising ecological balance over economic growth. Such a shift would likely necessitate a re-evaluation of the cognitive biases integrated into the decision-making framework, as new paradigms could introduce different biases or alter the significance of existing ones.

For instance, stakeholders might need to grapple with biases related to long-term thinking or risk aversion in the context of entirely new economic models that challenge traditional growth-oriented mindsets. CE is the framework analysed in Chapter 1 of this thesis, where stakeholders for sustainability are identified.

In the event of a sudden change within the CE system, such as a disruptive technological innovation, a global economic crisis, or a significant environmental event, the stability and assumptions underpinning the current CE framework could be thrown into disarray. These sudden changes might lead to rapid shifts in stakeholder priorities, resource availability, or regulatory environments, requiring the model to adapt quickly. For example, a breakthrough in material science that enables near-perfect recycling could drastically alter the dynamics of resource loops within the CE, making certain cognitive biases more or less relevant to decision-making processes.

Similarly, a sudden environmental catastrophe could force immediate shifts in resource management strategies, with biases like panic or short-termism potentially leading to suboptimal decisions.

Building flexibility and adaptability into the decision-making framework is essential to manage the risks associated with paradigm shifts or sudden changes in the CE system. This can be achieved by including scenario planning and stress-testing models against potential future states. By preparing for a variety of possible changes—whether incremental or radical—stakeholders can develop contingency plans that minimise the impact of these disruptions. Additionally, embedding a culture of continuous learning and feedback within CE organisations will help ensure they remain agile and responsive to changes. It is also recommended that the framework be updated with the latest technological advancements and shifts in socio-economic thinking, allowing for the integration of new insights into the decision-making process.

By proactively addressing the potential for paradigm shifts and sudden changes, the CE framework developed in this research would become more resilient and capable of thriving under various future conditions. Stakeholders would be better equipped to navigate disruptions, maintaining momentum toward sustainability goals despite

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uncertainty (Gallagher et al., 2020:181-195). Furthermore, recognising and planning for these changes could lead to innovative strategies that turn challenges into opportunities, such as leveraging new technologies or emerging economic models to enhance sustainability efforts. Ultimately, this approach would ensure that the CE remains relevant and effective in promoting long-term ecological and financial health, regardless of the shifts that may occur.

8.3. Conclusion

The study concludes that cognitive biases play a significant role in shaping sustainable decision-making within the CE. Key takeaways include:

- Significance of bias awareness: Recognising and addressing cognitive biases is essential for successfully implementing CE initiatives. By mitigating these biases, stakeholders can improve resource management and reduce environmental impacts.
- Media's influence on sustainability: Positive media influence is crucial for encouraging sustainable behaviours, whereas negative media can hinder progress. Strategies to leverage media for sustainability should be a priority.
- Policy and practice recommendations: The study offers practical suggestions for policymakers and practitioners to enhance sustainable decision-making. These include promoting media literacy, increasing public awareness of cognitive biases, and creating supportive environments for sustainability.

The leverage points in STS of the CE with biases are strategic areas within the system where a small change can lead to significant improvements in outcomes.

Identifying and utilising these leverage points can help to address cognitive biases and enhance sustainable decision-making effectively. Here are some key leverage points:

- Policy and regulation: Implementing bias-reducing policies: developing policies that mandate transparency in marketing practices and decision-making processes can help mitigate cognitive biases. Incentives for sustainable practices: incentivising companies to adopt circular practices can encourage more sustainable decision-making.
- Technology and data analytics: Advanced analytics: utilising big data and machine learning to identify patterns of bias in decision-making processes can help organisations make more objective decisions. Decision support systems: Implementing technology-based decision support systems incorporating bias-leveraging strategies can guide users towards more rational and sustainable choices.
- Organisational culture and structure: Promoting diversity: encouraging diverse teams can reduce groupthink and introduce multiple perspectives, which can counteract biases. Inclusive decision-making processes: structuring decision-

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making processes to be inclusive and participatory can ensure that diverse viewpoints are considered, reducing the influence of individual biases.

- Marketing and communication: Encouraging companies to adopt ethical marketing practices that do not exploit cognitive biases can lead to more sustainable consumer behaviour. Transparent communication: providing clear and transparent information about the sustainability of products and services can help consumers make better-informed decisions.
- Feedback mechanisms: Continuous monitoring and feedback: establishing feedback loops to monitor the impact of decisions and policies continuously can help identify and address biases as they arise. Adaptive management: using adaptive management strategies to adjust policies and practices based on feedback and new information can ensure continuous improvement in decision-making.
- Stakeholder engagement: Collaborative networks: building networks that involve various stakeholders, including consumers, businesses, and policymakers, can ensure a holistic approach to decision-making and reduce biases. Stakeholder dialogues: facilitating dialogues among stakeholders can help surface and address biases, leading to more balanced and sustainable outcomes.

By targeting these leverage points, STS within the CE can be optimised to leverage the influence of cognitive biases, leading to more effective and sustainable decision-making processes. The discussion of findings serves as a research synthesis, where each insight gained through DSR is evaluated and contextualised within the broader research landscape.
By understanding and addressing cognitive biases, stakeholders can better navigate the complexities of the CE, leading to more sustainable outcomes and contributing to the broader goals of sustainable development.

This chapter explores future research directions, suggesting further ways to expand and validate the study. It prepares the reader for the conclusions and recommendations in the next chapter.

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9. Conclusions and Recommendations

The final chapter summarises the research, discussing the conclusions drawn from the study. It highlights the contributions to theory and practice, limitations, and assumptions. This section fits into the DSR framework of the thesis, as shown in Figure 125.

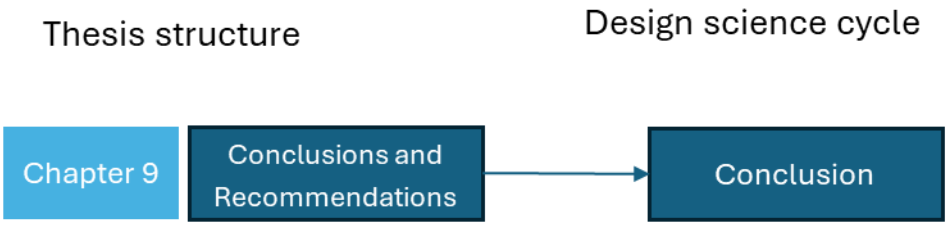

Figure 125. Design Science Research Framework - Chapter 9

Imagine designing a new, sustainable city from the ground up. The success of such an ambitious project depends not just on the technical infrastructure but also on how the inhabitants will interact with their environment, influenced by their cognitive biases. This thesis demonstrates the critical importance of integrating these biases into SE to create genuinely sustainable decision-making frameworks within the CE. This chapter recommends future research and practical applications that, like building a sustainable city, must continue to bridge the gap between technical solutions and human behaviour, ensuring that both aspects are harmonised for lasting impact.

9.1. Introduction

In this concluding chapter, it is essential to revisit key findings and insights gained throughout the research journey. This research aimed to explore the influence of cognitive biases on decision-making within the CE through the lens of SE and ST. As established in earlier chapters, the development of a novel framework that integrates cognitive biases into sustainable decision-making processes is pivotal for advancing the CE model. To provide a comprehensive reflection on the research objectives and outcomes, a referral back to several foundational sections is needed, including Chapter 1.4, which articulated the research problem statement, outlining the complexities of cognitive biases influencing stakeholder decisions in the CE.

Chapter 1.5 further detailed the research objectives, emphasising the need to systematically model and analyse decision-making influences, while Chapter 1.6 posed critical research questions that guided the investigation into how biases affect sustainability and stakeholder dynamics. Drawing from these sections, this chapter synthesises the research findings, discusses their implications for both theory and practice and presents recommendations for future work in the field. See Table 36 for a summary of novel contributions and how they relate to the RQs and ROs.

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In examining the intersection of STS and the CE, it was evident that social elements within the CE model were inherently biased towards sustainable decisions. The complexity of SE decisions was amplified by the involvement of numerous stakeholders, competing objectives, substantial uncertainty, and significant consequences. Previous research has demonstrated that cognitive biases could significantly distort stakeholder decisions. In the context of the CE, these stakeholders were both internal and external, making it imperative to understand and mitigate these biases to implement innovative models effectively.

This study aimed to fill a critical research gap in applying SE (particularly SSM) to decision-making within the CE. By developing a systematic framework for modelling, analysing, and managing decision-making in the CE, this research sought to establish a clear link between cognitive biases and unsustainable activities. The proposed framework leveraged these biases to promote more sustainable practices.

The research objectives guiding this study were identifying areas where control measures were needed to mitigate biased decision-making and conceptualise a model for sustainable decision-making in the CE. These objectives aimed to provide valuable insights for CE practitioners, sustainability program managers, and stakeholders, enhancing the effectiveness and efficiency of sustainability initiatives.

The research questions formulated to achieve these objectives included exploring the extent and influence of biases in sustainable decision-making, understanding the role of internal and external stakeholders within the CE framework, and examining how the adoption of CE practices affected stakeholder dynamics. Additionally, this study investigated the potential of BSD to uncover and address these biases through empirical survey data.

As the findings and implications of this research are presented, the following conclusions will highlight the critical insights gained, the practical applications of the developed framework, and the future directions for continued exploration in this vital area.

9.2. DSR Methodology Conclusion

The stock and flow model simulations comprehensively understood the complex interactions between cognitive biases, media influence, and sustainability-related behaviours within the CE. This research aimed to investigate the impact of cognitive biases on stakeholders' decision-making processes and identify potential interventions to promote sustainable practices.

Key findings from the simulation revealed that cognitive biases significantly influence stakeholders' perceptions and decisions.

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These biases shape individuals' perceived need for sustainability, affecting their responses to information and changes in behaviour. Positive media influence increased willingness to change habits and adopt sustainable behaviours, while negative media coverage reinforced existing biases and resistance to change.

9.3. Contributions to Theory and Practice

The practical implications of the research are substantial for policymakers, industry practitioners, and other stakeholders. By understanding the dynamics of biases and media influence on behaviour change, targeted strategies can be developed to promote sustainability and leverage the impact of cognitive biases. This research provides a framework for developing policies and practices that can effectively address and mitigate the influence of cognitive biases in decision-making processes.

Recommendations for addressing biases in decision-making include increasing public awareness of biases, promoting media literacy, and creating supportive environments for sustainable practices. Educating the public about common cognitive biases and how they influence decision-making can empower individuals to make more rational and sustainable choices. Promoting media literacy is crucial as it helps individuals critically evaluate the information they receive, reducing the likelihood of being swayed by biased or misleading content. Creating supportive environments involves designing systems and policies that encourage sustainable practices and make adopting them easier for individuals and organisations.

Moreover, integrating bias awareness training into organisational development programs can help industry practitioners recognise and mitigate their biases, leading to more objective and fair decision-making processes. Implementing decision-support tools that highlight potential biases and suggest alternative approaches can also be beneficial. Policymakers can use these insights to design regulations and incentives that encourage sustainable behaviours and reduce the impact of cognitive biases on policy decisions.

This research contributes to a deeper understanding of the factors that drive or hinder the CE's sustainable production and consumption. The insights gained from the simulation provide a foundation for advancing sustainability goals and creating a more resilient and equitable future. By identifying leverage points and potential interventions, stakeholders can better navigate the complexities of the CE and promote more sustainable outcomes.

For instance, identifying critical junctures where interventions can most effectively influence behaviour can help design targeted campaigns or policies that maximise impact.

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The practical implications also extend to the design of educational programs and public campaigns to foster a culture of sustainability. By incorporating findings on cognitive biases, these programs can be tailored to address specific misconceptions or habits that hinder sustainable practices. This can lead to a more informed and engaged public that is better equipped to make decisions and contribute to the CE.

Furthermore, industry practitioners can use the insights from this research to innovate and develop products and services that align with sustainable principles. By understanding the biases influencing consumer choices, businesses can design offerings that appeal to consumers' rational and emotional needs while promoting sustainable consumption patterns. This can drive market demand for sustainable products and contribute to the overall goals of the CE.

Overall, this research provides a robust framework for understanding and addressing the cognitive biases that influence decision-making in the context of the CE. By applying these insights, stakeholders can develop more effective strategies to promote sustainability, ensuring a more equitable and resilient future.

Table 36. Novel contribution discussion

Novel contributions of the thesis research	Why the novel may be useful	Relation of research objectives and the research questions	Applicable sections of the thesis
Development of a framework linking cognitive biases to sustainable decision-making in the CE	Helps stakeholders understand the impact of cognitive biases on sustainability decisions, thus improving sustainable practices	RO1: Identifying areas to leverage biased decision-making in the CE (Relates to RQ1, RQ2) RQ1 and RQ3 are separate and not combined because they focus on distinct aspects of biases in relation to sustainability and the CE.	Chapter 3: Model and Framework Development
Empirical validation of stakeholder decision alignment with sustainability goals	Validates the effectiveness of the framework and offers practical insights for policymakers and practitioners	RO2: Conceptualising a model for sustainable decision-making (Relates to RQ3, RQ4)	Chapter 7: Validation and Verification
Integration of Systems Thinking and System Dynamics to investigate biases in complex systems	Enhances the accuracy of systems models by incorporating human behavior and bias	RO1 and RO2: Bias and sustainability connections (Relates to RQ1, RQ5)	Chapter 4: Conceptual Model

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Application of Monte Carlo simulations and multi-criteria decision analysis to measure and mitigate biases	Offers quantitative tools to simulate real-world stakeholder decisions under uncertainty	RO1: Leveraging biased decision-making (Relates to RQ3, RQ5)	Chapter 6: Results and Data Analysis

The developed framework, which integrates cognitive biases into the CE decision-making process, has been empirically validated, showing a measurable increase in the effectiveness of sustainability initiatives. Specifically, the research demonstrated that by addressing cognitive biases, stakeholder decision-making can be aligned with sustainability goals more effectively, improving the implementation of CE practices.

Furthermore, this research offers a replicable model that can be adapted to various sectors within the CE, providing a significant tool for policymakers, engineers, and managers. These contributions advance the academic understanding of the interplay between cognitive biases and SE and offer tangible benefits to organisations aiming to implement more sustainable practices.

9.4. Limitations and Assumptions of the Research

This study's limitation includes the difficulty of transitioning from the LE to CE. This is because of the current consumer-based economy. Linear behaviour has been imparted into cultures and generations. Another limitation is generating demand for repaired, re-used, or recycled products (Bittar, 2018:527-536). This study is an initial phase in realising the advantages of improved sustainable decision-making.

Moreover, the complexity of cognitive biases themselves posed a limitation. The study focused on a select few biases, but numerous other biases may also significantly influence decision-making within the CE. Further research is necessary to explore a broader range of cognitive biases and their interactions.

Assumptions in this study include variable stakeholder mental models and the accuracy of existing decision-making models. Another fundamental belief was that stakeholders would be willing to adopt and apply the proposed frameworks and models. This assumption does not account for potential resistance to change or the influence of organisational culture on the acceptance of new methodologies.

Lastly, the study assumed that the interventions and strategies proposed would be universally applicable across different sectors and regions, which may overlook the unique challenges and contexts faced by various industries and geographic areas. Future research should tailor approaches to specific contexts to ensure their relevance and effectiveness.

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9.5. Future Recommendations

Future research should focus on expanding empirical studies to include a broader range of industries and geographic regions. By gathering more diverse data, researchers can better understand how cognitive biases and decision-making processes vary across contexts within the CE. This will help to validate and refine the conceptual models presented in this thesis.

Building on the findings of this study, future research should aim to develop and test practical interventions and strategies to leverage the impact of cognitive biases in decision-making. These strategies could include training programs, decision-support tools, and policy recommendations to enhance objectivity and fairness in individual and organisational decision-making processes. Future research could explore the role of cultural orientations in shaping cognitive biases related to CE adoption, as different cultural values and decision-making frameworks may influence sustainability perceptions and behaviours. Additionally, the integration of AI-driven decision support systems could serve as a digital System 2, mitigating cognitive biases by providing data-driven, objective insights that counteract heuristic-driven decision-making. Developing AI-powered sustainability frameworks could enhance bias-aware policy-making and corporate sustainability strategies, ensuring more rational and equitable decision-making processes in CE implementation.

Investigate the role of emerging technologies, such as artificial intelligence and machine learning, in identifying and reducing cognitive biases. Future studies should explore how these technologies can be integrated into the CE framework to improve decision-making efficiency and accuracy, promoting more sustainable and equitable outcomes.

Future research should also delve into the cultural dimensions of cognitive biases and decision-making within the CE. Examining how cultural norms and values influence stakeholder behaviours and decisions can provide deeper insights into designing more culturally sensitive and effective sustainability frameworks.

Additionally, more longitudinal studies are necessary to observe the long-term impacts of cognitive biases on decision-making within the CE. Such studies could track changes over time, offering a dynamic view of how biases evolve and how interventions can be adapted to maintain effectiveness.

Exploring interdisciplinary approaches that combine insights from psychology, economics, and environmental science could further enrich our understanding of cognitive biases in the CE. Integrating these diverse perspectives can lead to more holistic and innovative solutions for sustainable decision-making.

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Finally, there is a need for more research on the impact of regulatory environments on cognitive biases and decision-making within the CE. Understanding how different policy frameworks and regulations mitigate or exacerbate biases can guide the development of more supportive and bias-aware regulatory practices.

9.6. Conclusion

In an era where the global economy is being reshaped by information technology and digitisation, the relevance of STS is unparalleled. The mounting concerns regarding environmental sustainability and social challenges, coupled with the urgent need for sustainable practices, highlight the critical role of STS in navigating these complexities. However, the evolution of STS lags behind the rapid advancement of sustainability frameworks, such as the CE.

The CE presents a promising alternative to the LE advocating for reducing raw material extraction and recirculating resources to create value within biological and technological industries. The decision-making processes within STS are crucial for evaluating and implementing the most sustainable options within the CE framework. Sustainable decision-making involves various parameters, with marketing significantly influencing consumer behaviour through cognitive biases.

Despite the inherent rationality of consumer decisions, irrational tendencies often dominate, exacerbated by marketing strategies designed to exploit cognitive biases. This underscores the importance of making informed and rational decisions within our STS to achieve sustainability. As history has shown, technological transitions, such as the end of the Stone Age, are driven by the pursuit of better solutions rather than the depletion of resources. Today, we as people stand at a similar crossroads with sustainability and the CE. By making the right decisions within our STSs, we can ensure a sustainable future and avoid the exhaustion of our finite resources.

In conclusion, integrating STS and sustainability frameworks like the CE is imperative for addressing the global challenges of our time. By understanding and mitigating the impact of cognitive biases on decision-making, we can harness the full potential of sustainable practices and pave the way for a more resilient and equitable world. The opportunity is vast; we can transition to a sustainable future through thoughtful and strategic decision-making. The conclusions drawn from this study are the culmination of multiple research cycles within the DSR framework, each contributing to the overall research findings and practical implications.

Section 9 offers future recommendations for research and practical applications, ensuring the findings can be leveraged for continued progress towards sustainability in the CE.

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9.7. Chapter Summary

In Chapter 1, the background of the research study was discussed. This included the context of the research in an STS and why it is vital, according to recent literature, to re-evaluate the CE model to integrate the social impact and influences of stakeholders within the system.
Chapter 2 elaborated further on Chapter 1, with literature about sustainability, SE and cognitive biases. Beginning with the awareness of the problem from the DSR methodology, the research delved into a comprehensive review of existing literature and engaged stakeholders to articulate and define the intricacies of a real-world problem or opportunity. Current models and theories were described, and the importance thereof was elaborated on. The motivation of the chapter was to explore existing methods and models for topics found in literature and to identify how these can be interconnected and synthesised for the following chapter.

In Chapter 3, a detailed account of the construction and refinement of various models used in this research is presented. The models were designed to investigate the complex interactions within the CE and to analyse how cognitive biases influence decision-making processes. The chapter begins by outlining the theoretical foundations and methodologies that guide the model-building process, rooted in both DSR and SD. These approaches ensure that the models are iterative, practical, and aligned with real-world applications.

Each model is developed systematically, beginning with a Conceptual CE framework that integrates social, economic, and environmental dimensions, followed by the application of a Limits to Growth archetype that helps explore constraints on sustainable decision-making. A Stock and Flow diagram is also constructed to map the influence of cognitive biases on sustainability decisions, providing a dynamic representation of these relationships over time.

Throughout the chapter, empirical data, grounded theory coding, and ST methodologies are used to validate and refine the models. The chapter culminates in the integration of the CLD and SFD, which are synthesised to create a comprehensive, dynamic model capable of simulating decision-making in a CE context.

This chapter sets the foundation for the Conceptual Model in the next stage of the thesis, linking theoretical insights with practical, data-driven modelling. It highlights the novel contributions of the research by integrating cognitive biases and ST into sustainability models, filling gaps identified in the literature.

In Chapter 4, it was asserted that a conceptual model for sustainable decision-making can be conceptualised based on the literature and findings gathered in the previous chapters. This conceptual model was developed through boundary definitions, different

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systems approaches, and methods. Finally, the chapter concluded with a tangible model. The following chapters will create the model further with the research methods and data gathered. This step, the suggestions from the DSR methodology, involves the creative proposal of a novel solution backed by the development of conceptual models or frameworks.
Chapter 5 discussed the research methods used in the study. Firstly, the strategy and DSR methodology were addressed. A detailed description and evaluation of the surveys were discussed, and a summary of the research design was given. As the process advances to development, the focus shifts to the tangible creation of the proposed artefact, be it a system or a model, utilising established design principles and methodologies.

Chapter 6 presented the data and results from the methods discussed in the previous chapter. A comprehensive account of the data-gathering process was provided with a summarised version of the gathered data. The data analysis section of this chapter is the rational focus of the study. Different data analysis methods were discussed and applied in this chapter and validated in the next section. Moving forward, the evaluation step from the DSR methodology scrutinises the artefact's effectiveness and efficiency, entailing the establishment of evaluation frameworks and the execution of empirical studies or simulations.

In Chapter 7, data validation and verification were done by comparison. The final model was compared to the conceptual model of Chapter 3. The differences and similarities were discussed and analysed to conclude with a final model for a social-debiased CE model. Reflection ensued, inviting a critical analysis of the design and evaluation process, identifying strengths, weaknesses, and areas for enhancement. The reflective insights gleaned feed into the refinement of both the artefact and the underlying design principles. Subsequently, the communication step disseminates research results to the academic community and practitioners through scholarly publications and presentations at conferences or workshops.

The preceding section, Chapter 8, concluded the results discussion with explanations for further use of the model. The limitations and assumptions relevant to the research were discussed and explored to validate the study in the context of the preliminary decisions taken by the research. Future studies pertinent to expanding this research were discussed in this chapter before the study's conclusion.

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References

Abernethy, R. B. 2006. *The New Weibull handbook : reliability & statistical analysis for predicting life, safety, risk, support cost, failures, and forecasting warranty claims, substantiation and accelerated testing, using Weibull, Log normal, Crow-AMSAA, probit and Kaplan-Meier Models*, 5th, North Palm Beach (Florida): R.B. Abernethy.

Achakulwisut, P., Erickson, P., Guivarch, C., Schaeffer, R., Brutschin, E. & Pye, S. 2023. Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions. *Nature Communications,* 14(1)**,** pp 5425. https://doi.org/10.1038/s41467-023-41105-z

Ackerman, R., Bernstein, D. M. & Kumar, R. 2020. Metacognitive hindsight bias. *Memory & cognition,* 48(5)**,** pp 731-744. https://psycnet.apa.org/doi/10.3758/s13421-020-01012-w

Adams, K. R., Gibbs, L., Knott, N. A., Broad, A., Hing, M., Taylor, M. D. & Davis, A. R. 2020. Coexisting with sharks: a novel, socially acceptable and non-lethal shark mitigation approach. *Scientific Reports,* 10(1)**,** pp 17497. https://doi.org/10.1038/s41598-020-74270-y

Ahmad, H., Yaqub, M. & Lee, S. H. 2024. Environmental-, social-, and governance-related factors for business investment and sustainability: A scientometric review of global trends. *Environment, Development and Sustainability,* 26(2)**,** pp 2965-2987.

Aimone, E. 2024. *Assessing Community Perceptions of Hydrogen as a Fuel for Domestic Heating.* Worcester Polytechnic Institute.

Al-Emran, M. 2023. Beyond technology acceptance: Development and evaluation of technology-environmental, economic, and social sustainability theory. *Technology in Society,* 75(2-5.

Al-Emran, M. & Griffy-Brown, C. 2023. The role of technology adoption in sustainable development: Overview, opportunities, challenges, and future research agendas. *Technology in Society,* 73(102240. https://www.sciencedirect.com/science/article/pii/S0160791X23000453

Alessi, S. & Kopainsky, B. 2015. System dynamics and simulation/gaming: Overview. *Simulation & Gaming,* 46(3-4)**,** pp 223-229. https://doi.org/10.1177/1046878115596390

Alfred, P., Kosnik, B., Lacson, F., Merriman, S. C., O'Neil, C. M., Seely, O. & Thomas, J. 2017. Human Systems Integration Stakeholders: Successes, Challenges, and Lessons Learned Across Government and Industry. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* 61(1)**,** pp 1706-1710.

Allen, M. S., Robson, D. A., Martin, L. J. & Laborde, S. 2020. Systematic review and meta-analysis of self-serving attribution biases in the competitive context of

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organized sport. *Personality and Social Psychology Bulletin,* 46(7), pp 1027-1043. https://doi.org/10.1177/0146167219893995

Amicarelli, V. & Bux, C. 2023. Users' Perception of the Circular Economy Monitoring Indicators as Proposed by the UNI/TS 11820:2022: Evidence from an Exploratory Survey. *Environments,* 10(4), pp 1-16. https://www.mdpi.com/2076-3298/10/4/65

Anastasiou, A., Karagrigoriou, A. & Katsileros, A. 2020. Comparative evaluation of goodness of fit tests for normal distribution using simulation and empirical data. *Biometrical Letters,* 57(237-251.

Araújo, O. Q. F. & de Medeiros, J. L. 2021. How is the transition away from fossil fuels doing, and how will the low-carbon future unfold? *Clean Technologies and Environmental Policy,* 23(5), pp 1385-1388. https://doi.org/10.1007/s10098-021-02123-x

Aravindh, R. V. & Thirupathi, S. 2019. Data analysis in social sciences: comparison between quantitative and qualitative research. *International Journal of Management Research and Social Science*.

Armocida, A. M. 1992. The Seven Habits of Highly Effective People: By Stephen R. Covey. New York: Simon and Schuster, 1989. *NASSP Bulletin,* 76(542), pp 120-121. https://doi.org/10.1177/019263659207654222

Arnott, D. & Pervan, G. 2012. Design Science in Decision Support Systems Research: An Assessment using the Hevner, March, Park, and Ram Guidelines. *Journal of the Association of Information Systems,* 13(923-949. http://dx.doi.org/10.17705/1jais.00315

Arora, N. K. & Mishra, I. 2019. United Nations Sustainable Development Goals 2030 and environmental sustainability: race against time. *Environmental Sustainability,* 2(4), pp 339-342. https://doi.org/10.1007/s42398-019-00092-y

AtKisson, A. 2006. Sustainability Is Dead—Long Live Sustainability. *The Future of Sustainability,* 231–243. https://link.springer.com/chapter/10.1007/1-4020-4908-0_12

AtKisson, A. 2011. *The Sustainability Transformation : How to Accelerate Positive Change in Challenging Times*, London: Routledge. https://search.ebscohost.com/login.aspx?direct=true&db=nlebk&AN=466142&site=ehost-live&scope=site

Attanasio, G., Preghenella, N., De Toni, A. F. & Battistella, C. 2022. Stakeholder engagement in business models for sustainability: The stakeholder value flow model for sustainable development. *Business Strategy and the Environment,* 31(3), pp 860-874. https://onlinelibrary.wiley.com/doi/abs/10.1002/bse.2922

Awah, L. S., Nyam, Y. S., Belle, J. A. & Orimoloye, I. R. 2024. A system archetype approach to identify behavioural patterns in flood risk management: Case study

© University of Pretoria

of Cameroon. *Environmental Development,* 51(1-17. https://www.sciencedirect.com/science/article/pii/S2211464524000642

Bacher, J., Pihkola, H., Kujanpää, L. & Mroueh, U.-M. 2018. ADVANCING THE CIRCULAR ECONOMY THROUGH GROUP DECISION-MAKING AND STAKEHOLDER INVOLVEMENT. *Detritus,* In Press(1. http://dx.doi.org/10.31025/2611-4135/2018.13741

Baghaei Lakeh, A. & Ghaffarzadegan, N. 2016. The dual-process theory and understanding of stocks and flows. *System Dynamics Review,* 32(3-4)**,** pp 309-331. https://onlinelibrary.wiley.com/doi/abs/10.1002/sdr.1566

Bahill, A. T. & Gissing, B. 1998. Re-evaluating Systems Engineering Concepts Using Systems Thinking. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on,* 28(516-527. https://www.researchgate.net/publication/3421261_Re-evaluating_Systems_Engineering_Concepts_Using_Systems_Thinking

Bahill, A. T. & Madni, A. M. 2023. Overarching Process for Systems Engineering and Design. *Handbook of Model-Based Systems Engineering.* Springer.

Banack, H. R., Hayes-Larson, E. & Mayeda, E. R. 2021. Monte Carlo Simulation Approaches for Quantitative Bias Analysis: A Tutorial. *Epidemiologic Reviews,* 43(1)**,** pp 106-117. https://doi.org/10.1093/epirev/mxab012

Bano, R., Khiadani, M. & Nyam, Y. S. 2022. System archetypes underlying formal-informal urban water supply dynamics. *Water Resources Management,* 36(13)**,** pp 4995-5010.

Bansal, P. 2005. Evolving sustainably: A longitudinal study of corporate sustainable development. *Strategic management journal,* 26(3)**,** pp 197-218. https://www.jstor.org/stable/20142218

Barati, A. A., Pour, M. D. & Sardooei, M. A. 2023. Water crisis in Iran: A system dynamics approach on water, energy, food, land and climate (WEFLC) nexus. *Science of the Total Environment,* 882(2-6.

Barnabè, F. & Davidsen, P. I. 2019. Exploring the potentials of behavioral system dynamics: insights from the field. *Journal of Modelling in Management,* 15(1)**,** pp 339-364. https://doi.org/10.1108/JM2-03-2019-0081

Barrie, J., Anantharaman, M., Oyinlola, M. & Schröder, P. 2022. The circularity divide: What is it? And how do we avoid it? *Resources, Conservation and Recycling,* 180(106-208. http://dx.doi.org/10.1016/j.resconrec.2022.106208

Barton, M., Symborski, C., Quinn, M., Morewedge, C. K., Kassam, K. S. & Korris, J. H. 2016. The Use of Theory in Designing a Serious Game for the Reduction of Cognitive Biases. *Transactions of the Digital Games Research Association,* 2(3)**,** pp. http://dx.doi.org/10.26503/todigra.v2i3.53

© University of Pretoria

Bastons, M. & Armengou, J. 2017. Realism and Impartiality: Making Sustainability Effective in Decision-Making. *Science and Engineering Ethics,* 23(4)**,** pp 969-987. https://www.proquest.com/scholarly-journals/realism-impartiality-making-sustainability/docview/1925068394/se-2?accountid=14717
http://UnivofPretoria.on.worldcat.org/atoztitles/link?sid=ProQ:&issn=13533452&volume=23&issue=4&title=Science+and+Engineering+Ethics&spage=969&date=2017-08-01&atitle=Realism+and+Impartiality%3A+Making+Sustainability+Effective+in+Decision-Making&au=Bastons%2C+Miquel%3BArmengou%2C+Jaume&id=doi:10.1007%2Fs11948-016-9850-6

Bavel, J. J. V., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., Crockett, M. J., Crum, A. J., Douglas, K. M., Druckman, J. N., Drury, J., Dube, O., Ellemers, N., Finkel, E. J., Fowler, J. H., Gelfand, M., Han, S., Haslam, S. A., Jetten, J., Kitayama, S., Mobbs, D., Napper, L. E., Packer, D. J., Pennycook, G., Peters, E., Petty, R. E., Rand, D. G., Reicher, S. D., Schnall, S., Shariff, A., Skitka, L. J., Smith, S. S., Sunstein, C. R., Tabri, N., Tucker, J. A., Linden, S. v. d., Lange, P. v., Weeden, K. A., Wohl, M. J. A., Zaki, J., Zion, S. R. & Willer, R. 2020. Using social and behavioural science to support COVID-19 pandemic response. *Nature Human Behaviour,* 4(5)**,** pp 460-471. https://doi.org/10.1038/s41562-020-0884-z

Baxter, G. & Sommerville, I. 2010. Socio-technical systems: From design methods to systems engineering. *Interacting with Computers,* 23(1)**,** pp 4-17. https://doi.org/10.1016/j.intcom.2010.07.003

Belk, R. W. 1975. Situational variables and consumer behavior. *Journal of Consumer research,* 2(3)**,** pp 157-164.

Belton, V. & Stewart, T. 2010. Problem Structuring and Multiple Criteria Decision Analysis. http://dx.doi.org/10.1007/978-1-4419-5904-1_8

Belton, V., Stewart, T. J., Belton, V. & Stewart, T. J. 2002. An Integrated approach to MCDA. *Multiple Criteria Decision Analysis: An Integrated Approach,* 331-343. https://link.springer.com/chapter/10.1007/978-1-4615-1495-4_11

Benkert, J. 2021. Reframing business sustainability decision-making with value-focussed thinking. *Journal of Business Ethics,* 174(2)**,** pp 441-456.

Berkman, E. T. 2018. The Neuroscience of Goals and Behavior Change. *Consulting Psychology Journal,* 70(1)**,** pp 28-44.

Berthet, V. 2022. The Impact of Cognitive Biases on Professionals' Decision-Making: A Review of Four Occupational Areas. *Frontiers in Psychology,* 12(1-13. https://www.frontiersin.org/article/10.3389/fpsyg.2021.802439

Bhamra, T., Lilley, D. & Tang, T. 2011. Design for Sustainable Behaviour: Using Products to Change Consumer Behaviour. *The Design Journal,* 14(427-445. http://dx.doi.org/10.2752/175630611X13091688930453

© University of Pretoria

Bhattacharya, P. & Bhattacharjee, R. 2010. A study on Weibull distribution for estimating the parameters. *Journal of Applied Quantitative Methods,* 5(2)**,** pp 234-241.

Birkle, C., Pendlebury, D. A., Schnell, J. & Adams, J. 2020. Web of Science as a data source for research on scientific and scholarly activity. *Quantitative Science Studies,* 1(1)**,** pp 363-376.

Bittar, A. d. V. 2018. Selling remanufactured products: Does consumer environmental consciousness matter? *Journal of Cleaner Production,* 181(527-536.

Blanchard, B. S., Fabrycky, W. J. & Fabrycky, W. J. 1990. *Systems engineering and analysis*: Prentice hall Englewood Cliffs, NJ. https://www.researchgate.net/publication/241976516_Systems_Engineering_and_Analysis_Third_Edition

Bockstaller, C., Beauchet, S., Manneville, V., Amiaud, B. & Botreau, R. 2017. A tool to design fuzzy decision trees for sustainability assessment. *Environmental Modelling & Software,* 97(130-144. https://www.sciencedirect.com/science/article/pii/S1364815217302785

Bolis, I., Morioka, S. N. & Sznelwar, L. I. 2017. Are we making decisions in a sustainable way? A comprehensive literature review about rationalities for sustainable development. *Journal of Cleaner Production,* 145(310-322. https://www.sciencedirect.com/science/article/pii/S095965261730032X

Booher, H. R. & Beaton, R. J. 2009. Human Systems Integration. *Handbook of Systems Engineering and Management.* John Wiley & Sons.

Borland, H., Ambrosini, V., Lindgreen, A. & Vanhamme, J. 2016. Building Theory at the Intersection of Ecological Sustainability and Strategic Management. *Journal of Business Ethics,* 135(2)**,** pp 293-307. https://doi.org/10.1007/s10551-014-2471-6

Boyle, C., Head, P., Hood Am, D., Lawton, M., Lowe, I., O'Connor, M., Peet, J., Schreier, H. & Vanegas, J. 2013. Transitioning to sustainability: Pathways, directions and opportunities. *Int. J. of Sustainable Development,* 16(166-189. http://dx.doi.org/10.1504/IJSD.2013.056560

Bozeman III, J. F., Chopra, S. S., James, P., Muhammad, S., Cai, H., Tong, K., Carrasquillo, M., Rickenbacker, H., Nock, D., Ashton, W., Heidrich, O., Derrible, S. & Bilec, M. 2023. Three research priorities for just and sustainable urban systems: Now is the time to refocus. *Journal of Industrial Ecology,* 27(2)**,** pp 382-394. https://onlinelibrary.wiley.com/doi/abs/10.1111/jiec.13360

Braun, V. & Clarke, V. 2012. Thematic analysis. *In:* Cooper, H. (ed.) *Handbook of Research Methods in Psychology:.* American Psychological Association. http://dx.doi.org/10.1037/13620-004

© University of Pretoria

Braun, W. 2002. The system archetypes. *The Systems Modeling Workbook* https://www.albany.edu/faculty/gpr/PAD724/724WebArticles/sys_archetypes.pdf

Brenes-Peralta, L., Jiménez-Morales, M., Rodriguez, R., De Menna, F. & Vittuari, M. 2020. Decision-Making Process in the Circular Economy: A Case Study on University Food Waste-to-Energy Actions in Latin America. *Energies,* 9(13)**,** pp 2291. http://dx.doi.org/10.3390/en13092291

Brin, P. & Nehme, M. 2021. Sustainable development in emerging economy: Using the analytical hierarchy process for corporate social responsibility decision making. *Journal of information technology management,* 13(Special Issue: Role of ICT in Advancing Business and Management)**,** pp 159-174. https://jitm.ut.ac.ir/article_80744_1e9eb0beda4d8c3e7cb6defa1e8614fc.pdf

Brocklesby, J. 2016. The what, the why and the how of behavioural operational research—An invitation to potential sceptics. *European Journal of Operational Research,* 249(3)**,** pp 796-805. https://www.sciencedirect.com/science/article/pii/S0377221715008760

Brown, F. B., Martin, W. R. & Mosteller, R. D. Monte Carlo-advances and challenges. Workshop at PHYSOR-2008, Interlaken, Switzerland, 2008. 14-19.

Bureš, V. Mistakes in System Dynamics Models: An Educational Issues from the Systems Engineering Perspective. 2019. https://ieomsociety.org/pilsen2019/papers/388.pdf

Cabrera, D., Cabrera, L. L. & Midgley, G. 2023. The four waves of systems thinking. *Journal of Systems Thinking,* 1-51.

Cagno, E., Negri, M., Neri, A. & Giambone, M. 2023. One Framework to Rule Them All: An Integrated, Multi-level and Scalable Performance Measurement Framework of Sustainability, Circular Economy and Industrial Symbiosis. *Sustainable Production and Consumption,* 35(55-71. https://www.sciencedirect.com/science/article/pii/S2352550922002834

Calculli, C., D'Uggento, A. M., Labarile, A. & Ribecco, N. 2021. Evaluating people's awareness about climate changes and environmental issues: A case study. *Journal of Cleaner Production,* 324(129244. https://www.sciencedirect.com/science/article/pii/S0959652621034302

Caled, D. & Silva, M. J. 2022. Digital media and misinformation: An outlook on multidisciplinary strategies against manipulation. *Journal of Computational Social Science,* 5(1)**,** pp 123-159.

Calero Valdez, A., Ziefle, M. & Sedlmair, M. 2018. Studying Biases in Visualization Research: Framework and Methods. *Cognitive Biases in Visualizations.* Cham : Springer International Publishing : Springer. https://link.springer.com/chapter/10.1007/978-3-319-95831-6_2

© University of Pretoria

Camilleri, M. A., Cricelli, L., Mauriello, R. & Strazzullo, S. 2023. Consumer Perceptions of Sustainable Products: A Systematic Literature Review. *Sustainability,* 15(11)**,** pp 1-18. https://www.mdpi.com/2071-1050/15/11/8923

Canco, I., Kruja, D. & Iancu, T. 2021. AHP, a Reliable Method for Quality Decision Making: A Case Study in Business. *Sustainability,* 13(1-15.

Carey, G., Malbon, E., Carey, N., Joyce, A., Crammond, B. & Carey, A. 2015. Systems science and systems thinking for public health: a systematic review of the field. *BMJ Open,* 5(12)**,** pp. https://www.proquest.com/scholarly-journals/systems-science-thinking-public-health-systematic/docview/1860820890/se-2 http://UnivofPretoria.on.worldcat.org/atoztitles/link?sid=ProQ:&issn=&volume=5&issue=12&title=BMJ+Open&spage=&date=2015-01-01&atitle=Systems+science+and+systems+thinking+for+public+health%3A+a+systematic+review+of+the+field&au=Carey%2C+Gemma%3BMalbon%2C+Eleanor%3BCarey%2C+Nicole%3BJoyce%2C+Andrew%3BCrammond%2C+Brad%3BCarey%2C+Alan&id=doi:10.1136%2Fbmjopen-2015-009002

Carnegie, D. 2017. *How to win friends and influence people*, Sydney, NSW: HarperCollins Publishers Australia. https://dn720204.ca.archive.org/0/items/in.ernet.dli.2015.68346/2015.68346.How-To-Win-Friends-And-Influence-People--Ed11th_text.pdf

Cavana, R. Y., Delahaye, B. L. & Sekaran, U. 2001. *Applied Business research: Qualitative and Quantitative Methods*.

Chabowski, B. R., Gabrielsson, P., Hult, G. T. M. & Morgeson, F. V. 2023. Sustainable international business model innovations for a globalizing circular economy: a review and synthesis, integrative framework, and opportunities for future research. *Journal of International Business Studies,* 1-9. https://doi.org/10.1057/s41267-023-00652-9

Challender, S. 2000. Systems Thinking, Systems Practice. By Peter B. Checkland. Published by John Wiley, Chichester, UK, 1981, 330 pp., ISBN 0 471 27911 0 (republished 1999 in paperback, with a 30-year retrospective). From a practitioner perspective. *Systems Research and Behavioral Science,* 17(S1)**,** pp S78-S80. https://onlinelibrary.wiley.com/doi/abs/10.1002/1099-1743%28200011%2917%3A1%2B%3C%3A%3AAID-SRES384%3E3.0.CO%3B2-N

Chapin, F. S., Weber, E. U., Bennett, E. M., Biggs, R., van den Bergh, J., Adger, W. N., Crépin, A.-S., Polasky, S., Folke, C., Scheffer, M., Segerson, K., Anderies, J. M., Barrett, S., Cardenas, J.-C., Carpenter, S. R., Fischer, J., Kautsky, N., Levin, S. A., Shogren, J. F., Walker, B., Wilen, J. & de Zeeuw, A. 2022. Earth stewardship: Shaping a sustainable future through interacting policy and norm shifts. *Ambio,* 51(9)**,** pp 1907-1920. https://doi.org/10.1007/s13280-022-01721-3

Checkland, P. 1999. Systems thinking, systems practice. *Rethinking management information systems,* 45-56. http://cumincad.scix.net/cgi-bin/works/Show?91c4

© University of Pretoria

Checkland, P. & Poulter, J. 2006. *Learning for action : a short definitive account of soft systems methodology and its use for practitioner, teachers, and students*, Hoboken, NJ: Wiley. http://catdir.loc.gov/catdir/toc/ecip0611/2006010828.html

Chiappetta Jabbour, C. J., Seuring, S., Lopes de Sousa Jabbour, A. B., Jugend, D., De Camargo Fiorini, P., Latan, H. & Izeppi, W. C. 2020. Stakeholders, innovative business models for the circular economy and sustainable performance of firms in an emerging economy facing institutional voids. *Journal of Environmental Management,* 264(110416. https://www.sciencedirect.com/science/article/pii/S0301479720303509

Chu, D. S. 2013. Letter from Secretary Steven Chu to Energy Department Employees. *In:* Energy, D. o. (ed.). https://www.energy.gov/articles/letter-secretary-steven-chu-energy-department-employees.

Clark, V. L. P. 2019. Meaningful integration within mixed methods studies: Identifying why, what, when, and how. *Contemporary Educational Psychology,* 57(106-111. https://doi.org/10.1016/j.cedpsych.2019.01.007

Constantin, M. A., Schuurman, N. K. & Vermunt, J. K. 2023. A general Monte Carlo method for sample size analysis in the context of network models. *Psychological Methods,* 1-22.

Constantin, M. A., Schuurman, N. K. & Vermunt, J. K. 2023. A general Monte Carlo method for sample size analysis in the context of network models. *Psychological Methods*.

Constantino, S. M., Sparkman, G., Kraft-Todd, G. T., Bicchieri, C., Centola, D., Shell-Duncan, B., Vogt, S. & Weber, E. U. 2022. Scaling up change: a critical review and practical guide to harnessing social norms for climate action. *Psychological Science in the Public Interest,* 23(2)**,** pp 50-97.

Corbin, J. M. & Strauss, A. 2008. *Basics of Qualitative Research (3rd ed.): Techniques and Procedures for Developing Grounded Theory*: SAGE Publications. https://psycnet.apa.org/doi/10.4135/9781452230153

Cordella, M., Horn, R., Hong, S. H., Bianchi, M., Isasa, M., Harmens, R., Sonderegger, T. & Pihkola, H. 2023. Addressing sustainable development goals in life cycle sustainable assessment: Synergies, challenges and needs. *Journal of Cleaner Production,* 415(137719)**,** pp 3-8. https://www.sciencedirect.com/science/article/pii/S0959652623018772

Cornford, R., Spooner, F., McRae, L., Purvis, A. & Freeman, R. 2023. Ongoing over-exploitation and delayed responses to environmental change highlight the urgency for action to promote vertebrate recoveries by 2030. *Proceedings of the Royal Society B: Biological Sciences,* 290(1997)**,** pp 2-10. https://royalsocietypublishing.org/doi/abs/10.1098/rspb.2023.0464

© University of Pretoria

Corona, B., Shen, L., Reike, D., Carreón, J. R. & Worrell, E. 2019. Towards sustainable development through the circular economy-A review and critical assessment on current circularity metrics. *Resources Conservation and Recycling,* 151(https://doi.org/10.1016/j.resconrec.2019.104498

Covey, S. R. 1991. *The seven habits of highly effective people*: Free Press, New York,ISBN-10: 0743269519 ISBN-13: 978-0743269513. https://doi.org/10.1177/019263659207654222

Dash, B. M., Prakash, O. & Samantaray, A. K. 2023. Failure prognosis of the components with unlike degradation trends: A data-driven approach. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability,* 237(6)**,** pp 1132-1149. https://journals.sagepub.com/doi/abs/10.1177/1748006X221119301

Deming, W. E. 2000. *The New Economics for Industry, Government, Education*, Cambridge, USA: The MIT Press.

Deming, W. E. & Cahill, K. E. 2018. *The New Economics for Industry, Government, Education, third edition*: MIT Press. https://books.google.co.za/books?id=-iZyDwAAQBAJ

Denney, A. S. & Tewksbury, R. 2013. How to write a literature review. *Journal of criminal justice education,* 24(2)**,** pp 218-234. https://doi.org/10.1080/10511253.2012.730617

Desing, H., Brunner, D., Takacs, F., Nahrath, S., Frankenberger, K. & Hischier, R. 2020. A circular economy within the planetary boundaries: Towards a resource-based, systemic approach. *Resources, Conservation and Recycling,* 155(2-5. https://www.sciencedirect.com/science/article/pii/S0921344919305798

DeVellis, R. F. & Thorpe, C. T. 2022. *Scale development : theory and applications*, Fifth edition., Thousand Oaks, California: SAGE Publications, Inc. https://books.google.co.za/books/about/Scale_Development.html?id=vmwBHYuchfAC&redir_esc=y

Devins, D. W. & Medsker, L. R. 1982. *Energy: It's physical impact on the environment*, Chichester: John Wiley and Sons.

Dewulf, J. & Van Langenhove, H. 2006. *Renewables-based technology: sustainability assessment*: John Wiley & Sons. https://books.google.je/books?id=fTWV4XWa8k0C&printsec=frontcover&source=gbs_atb#v=onepage&q&f=false

Díaz-López, C., Martín-Blanco, C., De la Torre Bayo, J. J., Rubio-Rivera, B. & Zamorano, M. 2021. Analyzing the Scientific Evolution of the Sustainable Development Goals. *Applied Sciences,* 11(18)**,** pp 1-17. https://www.mdpi.com/2076-3417/11/18/8286

© University of Pretoria

Dietrich, D. M. & Olson, M. H. 1993. A Demonstration of Hindsight Bias Using the Thomas Confirmation Vote. *Psychological Reports,* 72(377 - 378. https://doi.org/10.2466/pr0.1993.72.2.377

Doyle, J. K., Radzicki, M. J. & Trees, W. S. 2008. Measuring Change in Mental Models of Complex Dynamic Systems. *In:* Qudrat-Ullah, H., Spector, J. M. & Davidsen, P. I. (eds.) *Complex Decision Making: Theory and Practice.* Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-73665-3_14

Dragolea, L.-L., Butnaru, G. I., Kot, S., Zamfir, C. G., Nuţă, A.-C., Nuţă, F.-M., Cristea, D. S. & Ştefănică, M. 2023. Determining factors in shaping the sustainable behavior of the generation Z consumer. *Frontiers in Environmental Science,* 11(1-18.

Eberhardt-Toth, E. & Wasieleski, D. M. 2013. A cognitive elaboration model of sustainability decision making: Investigating financial managers' orientation toward environmental issues. *Journal of Business Ethics,* 117(4)**,** pp 735-751.

Ehrlinger, J., Readinger, W. O. & Kim, B. 2016. Decision-Making and Cognitive Biases. *Encyclopedia of Mental Health*.

Eidin, E., Bielik, T., Touitou, I., Bowers, J., McIntyre, C., Damelin, D. & Krajcik, J. 2024. Thinking in terms of change over time: opportunities and challenges of using system dynamics models. *Journal of Science Education and Technology,* 33(1)**,** pp 1-28.

El-Taliawi, O. G. & Hartley, K. 2021. The COVID-19 crisis and complexity: A soft systems approach. *Journal of Contingencies and Crisis Management,* 29(1)**,** pp 104-107. https://doi.org/10.1111/1468-5973.12337

ElAlfy, A., Palaschuk, N., El-Bassiouny, D., Wilson, J. & Weber, O. 2020. Scoping the evolution of corporate social responsibility (CSR) research in the sustainable development goals (SDGs) era. *Sustainability,* 12(14)**,** pp 5544. https://doi.org/10.3390/su12145544

Ellis, G. 2018. So, what are cognitive biases? *Cognitive biases in visualizations.* Springer. https://doi.org/10.1007/978-3-319-95831-6_1

Elmor, L., Ramos, G. A., Vieites, Y., Andretti, B. & Andrade, E. B. 2024. Environmental sustainability considerations (or lack thereof) in consumer decision making. *International Journal of Research in Marketing,* 1-26.

Emery, F. 1993. Characteristics of Socio-Technical Systems. *In:* Eric, T., Hugh, M. & Beulah, T. (eds.) *The Social Engagement of Social Science, a Tavistock Anthology, Volume 2.* Philadelphia: University of Pennsylvania Press. https://doi.org/10.9783/9781512819052-009

EMF. 2017. *What is the Circular Economy?* [Online]. Available: https://www.ellenmacarthurfoundation.org/circular-economy/what-is-the-circular-economy.

© University of Pretoria

EMF. 2019. Completing the Picture: How the Circular Economy Tackles Climate Change, http://www.ellenmacarthurfoundation.org/publications

Enke, B., Gneezy, U., Hall, B., Martin, D., Nelidov, V., Offerman, T. & Van De Ven, J. 2023. Cognitive biases: Mistakes or missing stakes? *Review of Economics and Statistics,* 105(4)**,** pp 818-832.

Erdinç, P., Buduneli, Z., Gerşil, Ç., Erton, C., Paldrak, M. & Staiou, E. Analytic Hierarchy Process (AHP) and Goal Programming Approach for a Real-Life Supplier Selection Problem. 2024 Cham. Springer Nature Switzerland, 688-703.

Evans, D., Welch, D. & Swaffield, J. 2017. Constructing and mobilizing 'the consumer': Responsibility, consumption and the politics of sustainability. *Environment and Planning A,* 49(1396-1411. https://doi.org/10.1177/0308518X17694030

Evans, J. S. B. T. 2003. In two minds: dual-process accounts of reasoning. *Trends in Cognitive Sciences,* 7(10)**,** pp 454-459. https://www.sciencedirect.com/science/article/pii/S1364661303002250

Fares, W. H. 2014. The 'availability' bias: underappreciated but with major potential implications. *Critical care (London, England),* 18(2)**,** pp 118. https://doi.org/10.1186/cc13763

Fazey, I. & Leicester, G. 2022. Archetypes of system transition and transformation: Six lessons for stewarding change. *Energy Research & Social Science,* 91(5-11. https://www.sciencedirect.com/science/article/pii/S2214629622001505

Felmban, W. S. 2015. *The role of information and reflection in reducing the bias blind spot: A cross-cultural study.* University of Northern Colorado.

Fenton, N. & Neil, M. 2011. The use of Bayes and causal modelling in decision making, uncertainty and risk. *CEPIS Upgrade,* 12(5)**,** pp 10-21. https://www.researchgate.net/publication/228941964_The_use_of_Bayes_and_causal_modelling_in_decision_making_uncertainty_and_risk

Fletcher, G. & Griffiths, M. 2020. Digital transformation during a lockdown. *International journal of information management,* 55(102185.

Ford, R. C. & Richardson, W. D. 1994. Ethical decision making: A review of the empirical literature. *Journal of business ethics,* 13(3)**,** pp 205-221.

Forrester, J., Taylor, R., Pedoth, L. & Matin, N. 2018. Wicked problems. *Framing Community Disaster Resilience,* 61-75. https://www.researchgate.net/profile/Richard-Taylor-48/publication/328920778_Wicked_Problems_Resources_Capacities_Learning_and_Action/links/5ffc508192851c13fe0369bc/Wicked-Problems-Resources-Capacities-Learning-and-Action.pdf

© University of Pretoria

Forrester, J. W. 1961. *Industrial dynamics*. https://books.google.co.za/books?id=4CgzAAAAMAAJ

Freeman, R. E. 2020. The stakeholder approach revisited. *Wirtschafts-und unternehmensethik.* https://doi.org/10.1007/978-3-658-16205-4_55

Gallagher, V. C., Porter, T. H. & Gallagher, K. P. 2020. Sustainability change agents: leveraging political skill and reputation. *Journal of Organizational Change Management,* 33(1)**,** pp 181-195. https://doi.org/10.1108/JOCM-01-2018-0031

Gao, J. X., Barzel, B. & Barabási, A. L. 2016. Universal resilience patterns in complex networks. *Nature,* 530(7590)**,** pp 307-312. https://doi.org/10.1038/nature16948

Garcia-Saravia Ortiz-de-Montellano, C., Samani, P. & van der Meer, Y. 2023. How can the circular economy support the advancement of the Sustainable Development Goals (SDGs)? A comprehensive analysis. *Sustainable Production and Consumption,* 40(352-362. https://www.sciencedirect.com/science/article/pii/S2352550923001598

García, J. M. 2023. *Theory and Practical Exercises of System Dynamics: Modeling and Simulation with Vensim PLE. Preface John Sterman*: Juan Martin Garcia.

Gârdan, I. P., Micu, A., Paștiu, C. A., Micu, A. E. & Gârdan, D. A. 2023. Consumers' attitude towards renewable energy in the context of the energy crisis. *Energies,* 16(2)**,** pp 676.

Gary, M. S. & Wood, R. E. 2011. MENTAL MODELS, DECISION RULES, AND PERFORMANCE HETEROGENEITY. *Strategic Management Journal,* 32(6)**,** pp 569-594. http://www.jstor.org/stable/27975923

Geels, F. W., Sovacool, B. K., Schwanen, T. & Sorrell, S. 2017. Sociotechnical transitions for deep decarbonization. *Science,* 357(6357)**,** pp 1242-1244. https://core.ac.uk/download/pdf/96840074.pdf

Geissdoerfer, M., Savaget, P., Bocken, N. M. P. & Hultink, E. J. 2017. The Circular Economy A new sustainability paradigm? *Journal of Cleaner Production,* 143(757-768. https://doi.org/10.1016/j.jclepro.2016.12.048

Gifford, R. & Nilsson, A. 2014. Personal and social factors that influence pro-environmental concern and behaviour: A review. *International Journal of Psychology,* 49(3)**,** pp 141-157. https://doi.org/10.1002/ijop.12034

Gilovich, T., Griffin, D. W. & Kahneman, D. 2002. *Heuristics and biases : the psychology of intuitive judgment*, Cambridge, U.K. ;: Cambridge University Press. http://catdir.loc.gov/catdir/samples/cam033/2001037860.html
https://www.loc.gov/catdir/toc/cam025/2001037860.html
http://catdir.loc.gov/catdir/description/cam022/2001037860.html

© University of Pretoria

Gimeno, J. Á., Llera-Sastresa, E. & Scarpellini, S. 2020. A Heuristic Approach to the Decision-Making Process of Energy Prosumers in a Circular Economy. *Applied Sciences,* 10(19)**,** pp 68-69. https://www.mdpi.com/2076-3417/10/19/6869

Gladwell, M. 2005. *Blink : the power of thinking without thinking*: First edition. New York : Little, Brown and Co., 2005. https://search.library.wisc.edu/catalog/999992971702121

Glaser, B. G. 2002. Constructivist Grounded Theory? *Forum Qualitative Sozialforschung / Forum: Qualitative Social Research,* 3(3)**,** pp 9-21. https://www.qualitative-research.net/index.php/fqs/article/view/825

Gonella, J. d. S. L., Godinho Filho, M., Ganga, G. M. D., Latan, H. & Chiappetta Jabbour, C. J. 2024. A behavioral perspective on circular economy awareness: The moderating role of social influence and psychological barriers. *Journal of Cleaner Production,* 441(141062. https://www.sciencedirect.com/science/article/pii/S0959652624005092

Gordon, F. 2018. The Significance and Impact of the Media in Contemporary Society. *In:* Gordon, F. (ed.) *Children, Young People and the Press in a Transitioning Society: Representations, Reactions and Criminalisation.* London: Palgrave Macmillan UK. https://doi.org/10.1057/978-1-137-60682-2_2

Greene, R. 2000. The 48 laws of power. http://www.books24x7.com/marc.asp?bookid=43060

Greer, R., von Wirth, T. & Loorbach, D. 2023. The Circular Decision-Making Tree: an Operational Framework. *Circular Economy and Sustainability,* 3(2)**,** pp 693-718. https://doi.org/10.1007/s43615-022-00194-6

Gregor, S. & Hevner, A. 2013. Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly,* 37(337-356.

Grigore, G., Molesworth, M., Vontea, A., Basnawi, A. H., Celep, O. & Jesudoss, S. P. 2021. Corporate Social Responsibility in Liquid Times: The Case of Romania. *Journal of Business Ethics,* 174(4)**,** pp 763-782. https://doi.org/10.1007/s10551-021-04926-w

Groves, R. M., Fowler, F. J., Couper, M., Lepkowski, J. M., Singer, E. & Tourangeau, R. 2009. *Survey methodology*, Second edition, Hoboken, N.J.: Wiley.

Guemouria, A., Chehbouni, A., Belaqziz, S., Epule Epule, T., Ait Brahim, Y., El Khalki, E. M., Dhiba, D. & Bouchaou, L. 2023. System dynamics approach for water resources management: A case study from the Souss-Massa Basin. *Water,* 15(8)**,** pp 1-27.

Gurau, C. 2015. The effect of marketing promotions on customers' cognitive biases. *The Proceedings of the International Conference, Marketing - from Information to Decision,* 48+.

© University of Pretoria

https://link.gale.com/apps/doc/A438290608/AONE?u=anon~5e7a49f&sid=googleScholar&xid=e49411d4

Guzzo, D., Jamsin, E., Balkenende, R. & Costa, J. 2019. *The use of System Dynamics to verify long-term behaviour and impacts of circular business models: a sharing platform in healthcare*.

Haberfellner, R., de Weck, O., Fricke, E. & Vössner, S. 2019. Systems Thinking. *In:* Haberfellner, R., de Weck, O., Fricke, E. & Vössner, S. (eds.) *Systems Engineering: Fundamentals and Applications.* Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-13431-0_1

Halawa, E. 2024. Sustainable Energy: Concept and Definition in the Context of the Energy Transition—A Critical Review. *Sustainability,* 16(4)**,** pp 1-14.

Haleem, F., Farooq, S., Cheng, Y. & Waehrens, B. V. 2022. Sustainable Management Practices and Stakeholder Pressure: A Systematic Literature Review. *Sustainability,* 14(4)**,** pp 1967. https://doi.org/10.3390/su14041967

Hallett, L. M. & Hobbs, R. J. 2020. Thinking systemically about ecological interventions: what do system archetypes teach us? *Restoration Ecology,* 28(5)**,** pp 1017-1025.

Hämäläinen, R. P. 2015. Behavioural issues in environmental modelling–The missing perspective. *Environmental Modelling & Software,* 73(244-253. https://doi.org/10.1016/j.envsoft.2015.08.019

Hamed, R. S., Al-Shattarat, B. K., Al-Shattarat, W. K. & Hussainey, K. 2022. The impact of introducing new regulations on the quality of CSR reporting: Evidence from the UK. *Journal of International Accounting, Auditing and Taxation,* 46(2-13. https://www.sciencedirect.com/science/article/pii/S1061951821000690

Hao, C., Nyaranga, M. S. & Hongo, D. O. 2022. Enhancing Public Participation in Governance for Sustainable Development: Evidence From Bungoma County, Kenya. *Sage Open,* 12(1)**,** pp 1-11. https://journals.sagepub.com/doi/abs/10.1177/21582440221088855

Hardin, G. 1968. The tragedy of the commons: the population problem has no technical solution; it requires a fundamental extension in morality. *science,* 162(3859)**,** pp 1243-1248.

Hartley, K., van Santen, R. & Kirchherr, J. 2020. Policies for transitioning towards a circular economy: Expectations from the European Union (EU). *Resources, Conservation and Recycling,* 155(3-6. https://www.sciencedirect.com/science/article/pii/S0921344919305403

Hase, V., Mahl, D., Schäfer, M. S. & Keller, T. R. 2021. Climate change in news media across the globe: An automated analysis of issue attention and themes in climate change coverage in 10 countries (2006–2018). *Global Environmental*

© University of Pretoria

Change, 70(102353. https://www.sciencedirect.com/science/article/pii/S0959378021001321

Hayibor, S. & Wasieleski, D. M. 2009. Effects of the use of the availability heuristic on ethical decision-making in organizations. *Journal of Business Ethics,* 84(151-165. http://dx.doi.org/10.1007/s10551-008-9690-7

Head, B. W. & Alford, J. 2015. Wicked Problems: Implications for Public Policy and Management. *Administration & Society,* 47(6), pp 711-739. http://dx.doi.org/10.1177/0095399713481601

Heiskanen, E., Thidell, Å. & Rodhe, H. 2016. Educating sustainability change agents: the importance of practical skills and experience. *Journal of Cleaner Production,* 123(218-226. https://www.sciencedirect.com/science/article/pii/S0959652615017291

Herrera, P. A., Marazuela, M. A. & Hofmann, T. 2022. Parameter estimation and uncertainty analysis in hydrological modeling. *WIREs Water,* 9(1), pp 1-6. https://wires.onlinelibrary.wiley.com/doi/abs/10.1002/wat2.1569

Hevner, A. R., Parsons, J., Brendel, A. B., Lukyanenko, R., Tiefenbeck, V., Tremblay, M. C. & vom Brocke, J. 2024. Transparency in design science research. *Decision Support Systems,* 182(1-10.

Hjorth, P. & Bagheri, A. 2006. Navigating towards sustainable development: A system dynamics approach. *Futures,* 38(1), pp 74-92. https://www.sciencedirect.com/science/article/pii/S0016328705000753

Ho, C. M. 2019. A dangerous concoction: Pharmaceutical marketing, cognitive biases, and first amendment overprotection. *Indiana Law Journal,* 94(3), pp 773-854. https://www.repository.law.indiana.edu/ilj/vol94/iss3/1/

Hu, Y., He, X. & Poustie, M. 2018. Can Legislation Promote a Circular Economy? A Material Flow-Based Evaluation of the Circular Degree of the Chinese Economy. *Sustainability,* 10(4), pp 990. https://www.mdpi.com/2071-1050/10/4/990

Hunziker, S. & Blankenagel, M. 2024. Design Science Research Design. http://dx.doi.org/10.1007/978-3-658-42739-9_6

Imtiaz, S. A. 2023. Model equations and modeling methodology. *Modelling of Chemical Process Systems.* Elsevier.

Inigo, E. A. & Blok, V. 2019. Strengthening the socio-ethical foundations of the circular economy: Lessons from responsible research and innovation. *Journal of Cleaner Production,* 233(280-291. https://www.sciencedirect.com/science/article/pii/S0959652619320062

Ison, R., Blackmore, C. & Iaquinto, B. L. 2013. Towards systemic and adaptive governance: Exploring the revealing and concealing aspects of contemporary

© University of Pretoria

social-learning metaphors. *Ecological Economics,* 87(34-42. https://www.sciencedirect.com/science/article/pii/S0921800912004995

Ivanaj, S. 2024. Public information as a catalyst for individual-level behavior to mitigate climate change. *Journal of Cleaner Production,* 434(3. https://www.sciencedirect.com/science/article/pii/S0959652623041872

Izzo, J. B. & Vanderwielen, J. 2018. The purpose revolution : how leaders create engagement and competitive advantage in an age of social good. First edition. ed. Oakland, CA: Berrett-Koehler Publishers.

Jackson, M. C. 1994. Critical systems thinking: Beyond the fragments. *System Dynamics Review,* 10(2-3)**,** pp 213-229. https://onlinelibrary.wiley.com/doi/abs/10.1002/sdr.4260100209

James, P. 2022. Re-embedding the circular economy in Circles of Social Life: beyond the self-repairing (and still-rapacious) economy. *Local Environment,* 1-17. https://doi.org/10.1080/13549839.2022.2040469

Jamroz, B. F. & Williams, D. F. 2020. Consistency in Monte Carlo Uncertainty Analyses*. *Metrologia,* 57(6)**,** pp 1-8. https://dx.doi.org/10.1088/1681-7575/aba5aa

Javanmardi, E., Liu, S. & Xie, N. 2023. Exploring the Challenges to Sustainable Development from the Perspective of Grey Systems Theory. *Systems,* 11(2)**,** pp 70. https://www.mdpi.com/2079-8954/11/2/70

Johannesson, P. & Perjons, E. 2021. A Method Framework for Design Science Research. *In:* Johannesson, P. & Perjons, E. (eds.) *An Introduction to Design Science.* Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-78132-3_4

Kahneman, D., Lovallo, D. & Sibony, O. 2011. Before you make that big decision. *Harvard business review,* 89(50-60, 137. https://pubmed.ncbi.nlm.nih.gov/21714386/

Kalutara, P., Zhang, G., Setunge, S. & Wakefield, R. 2018. Prioritising sustainability factors for Australian community buildings' management using Analytical Hierarchy Process (AHP). *International Journal of Strategic Property Management,* 22(1)**,** pp 37-50. https://www.proquest.com/scholarly-journals/prioritising-sustainability-factors-australian/docview/2296155351/se-2?accountid=14717
http://UnivofPretoria.on.worldcat.org/atoztitles/link?sid=ProQ:&issn=1648715X&volume=22&issue=1&title=International+Journal+of+Strategic+Property+Management&spage=37&date=2018-03-01&atitle=Prioritising+sustainability+factors+for+Australian+community+buildings%E2%80%99+management+using+Analytical+Hierarchy+Process+%28AHP%29&au=Kalutara%2C+Pushpitha%3BZhang%2C+Guomin%3BSetunge%2C+Sujeeva%3BWakefield%2C+Ron&id=doi:10.3846%2Fijspm.2018.318

© University of Pretoria

Kannengießer, S. 2021. Media Reception, Media Effects and Media Practices in Sustainability Communication: State of Research and Research Gaps. *In:* Weder, F., Krainer, L. & Karmasin, M. (eds.) *The Sustainability Communication Reader: A Reflective Compendium.* Wiesbaden: Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-31883-3_18

Kannengiesser, U. & Gero, J. 2019. Empirical Evidence for Kahneman's System 1 and System 2 Thinking in Design. *Conference: Human Behaviour in Design,* 2-10. https://www.researchgate.net/publication/330764830_Empirical_Evidence_for_Kahneman's_System_1_and_System_2_Thinking_in_Design

Karschin, I. & Geldermann, J. 2015. Efficient cogeneration and district heating systems in bioenergy villages: an optimization approach. *Journal of Cleaner Production,* 104(305-314. https://www.sciencedirect.com/science/article/pii/S0959652615003261

Kasin, R., Wattana, C., Tony, G. & Jettarat, J. 2023. Evaluation of Sourcing Decision for Hydrogen Supply Chain Using an Integrated Multi-Criteria Decision Analysis (MCDA) Tool. 12. Available: https://doi.org/10.3390/resources12040048.

Kazancoglu, Y., Ozkan-Ozen, Y. D., Mangla, S. K. & Ram, M. 2020. Risk assessment for sustainability in e-waste recycling in circular economy. *Clean Technologies and Environmental Policy,* 1-13.

Kerr, J. R. & Wilson, M. S. 2018. Changes in perceived scientific consensus shift beliefs about climate change and GM food safety. *PLoS One,* 13(7)**,** pp 200.

Khaitan, S. K. & McCalley, J. D. 2015. Design Techniques and Applications of Cyberphysical Systems: A Survey. *Ieee Systems Journal,* 9(2)**,** pp 350-365. http://dx.doi.org/10.1109/JSYST.2014.2322503

Khatibi, F. S., Dedekorkut-Howes, A., Howes, M. & Torabi, E. 2021. Can public awareness, knowledge and engagement improve climate change adaptation policies? *Discover Sustainability,* 2(1)**,** pp 18. https://doi.org/10.1007/s43621-021-00024-z

Kienzler, M. 2018. Value-based pricing and cognitive biases : An overview for business markets. *Industrial Marketing Management,* 68(86-94. http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-141951

Kiger, M. E. & Varpio, L. 2020. Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher,* 42(8)**,** pp 846-854. https://doi.org/10.1080/0142159X.2020.1755030

Kim, D.-H. & Byung-Kwan, K. 2004. Cognitive Biases in Perceiving Feedback Loop Dominance. 2-7.

Kim, D. H. 1992. *System Archetypes I: Diagnosing Systemic Issues and Designing High-Leverage Interventions*. https://thesystemsthinker.com/systems-archetypes-i-diagnosing-systemic-issues-and-designing-interventions/

© University of Pretoria

Kirchherr, J., Reike, D. & Hekkert, M. 2017. Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling,* 127(221-232. https://www.sciencedirect.com/science/article/pii/S0921344917302835

Klaniecki, K., Wuropulos, K. & Hager, C. 2018. Behaviour Change for Sustainable Development.

Klein, G. A., Calderwood, R. & MacGregor, D. 1989. Critical decision method for eliciting knowledge. *IEEE Transactions on Systems, Man, and Cybernetics,* 19(3), pp 462-472.

Klímová, V. & Zitek, V. 2017. Intensity and Structure of Research and Development in the Czech and Slovak Regions. *Interdisciplinary Description of Complex Systems,* 15(36-48.

Kopnina, H. 2019. Towards Ecological Management: Identifying Barriers and Opportunities in Transition from Linear to Circular Economy. *Philosophy of Management,* 1-15.

Korhonen, J., Nuur, C., Feldmann, A. & Birkie, S. E. 2018. Circular economy as an essentially contested concept. *Journal of Cleaner Production,* 175(544-552. https://www.sciencedirect.com/science/article/pii/S0959652617330706

Korteling, J., Paradies, G. L. & Sassen-van Meer, J. P. 2023. Cognitive bias and how to improve sustainable decision making. *Frontiers in Psychology,* 14(1129835), pp 1-14.

Korteling, J. E. H., Paradies, G. L. & Sassen-van Meer, J. P. 2023. Cognitive bias and how to improve sustainable decision making. *Front Psychol,* 14(1129835.

Kotrlik, J. & Higgins, C. 2001. Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *Information technology, learning, and performance journal,* 19(1), pp 43-50. https://www.opalco.com/wp-content/uploads/2014/10/Reading-Sample-Size1.pdf

Krauss, J. 2018. Doughnut Economics: 7 Ways to Think Like a 21st Century Economist. *Journal of World - Systems Research,* 24(2), pp 452-457. https://www.proquest.com/scholarly-journals/doughnut-economics-7-ways-think-like-21st-century/docview/2138492424/se-2?accountid=14717
http://UnivofPretoria.on.worldcat.org/atoztitles/link?sid=ProQ:&issn=&volume=24&issue=2&title=Journal+of+World+-+Systems+Research&spage=452&date=2018-01-01&atitle=Doughnut+Economics%3A+7+Ways+to+Think+Like+a+21st+Century+Economist&au=Krauss%2C+Judith&id=doi:10.5195%2FJWSR.2018.854

Kreitz, C., Pugnaghi, G. & Memmert, D. 2020. Guessing right: Preconscious processing in inattentional blindness. *Quarterly Journal of Experimental Psychology,* 73(7), pp 1055-1065. https://doi.org/10.1177/1747021820911324

© University of Pretoria

Krejcie, R. V. & Morgan, D. W. 1970. Determining sample size for research activities. *Educational and psychological measurement,* 30(3)**,** pp 607-610. https://doi.org/10.1177/001316447003000308

Kroese, D. P., Brereton, T., Taimre, T. & Botev, Z. I. 2014. Why the Monte Carlo method is so important today. *Wiley Interdisciplinary Reviews: Computational Statistics,* 6(6)**,** pp 386-392.

Kuckartz, U. & Rädiker, S. 2019. Analyzing (Online) Survey Data with Closed and Open-Ended Questions.

Kueppers, M., Paredes Pineda, S. N., Metzger, M., Huber, M., Paulus, S., Heger, H. J. & Niessen, S. 2021. Decarbonization pathways of worldwide energy systems – Definition and modeling of archetypes. *Applied Energy,* 285(2-16. https://www.sciencedirect.com/science/article/pii/S0306261921000064

Kumar, P., Singh, R. K. & Kumar, V. 2021. Managing supply chains for sustainable operations in the era of industry 4.0 and circular economy: Analysis of barriers. *Resources, Conservation and Recycling,* 164(105215. https://www.sciencedirect.com/science/article/pii/S0921344920305322

Kumar, S., Kumar, N. & Vivekadhish, S. 2016. Millennium Development Goals (MDGs) to Sustainable Development Goals (SDGs): Addressing Unfinished Agenda and Strengthening Sustainable Development and Partnership. *Indian J Community Med,* 41(1)**,** pp 1-4. https://doi.org/10.4103/0970-0218.170955

Kunche, A. & Mielczarek, B. 2021. Application of System Dynamic Modelling for Evaluation of Carbon Mitigation Strategies in Cement Industries: A Comparative Overview of the Current State of the Art. *Energies,* 14(1464.

Kwakkel, J. H., Haasnoot, M. & Walker, W. E. 2016. Comparing robust decision-making and dynamic adaptive policy pathways for model-based decision support under deep uncertainty. *Environmental Modelling & Software,* 86(168-183. https://doi.org/10.1016/J.ENVSOFT.2016.09.017

Laissue, N. & Kovic, M. 2016. *Consuming rationally: How marketing is exploiting our cognitive biases, and what we can do about it* [Online]. Swiss Skeptics Discussion Paper Series. Available: https://www.researchgate.net/publication/312116633_Consuming_rationally_How_marketing_is_exploiting_our_cognitive_biases_and_what_we_can_do_about_it [Accessed 3 1].

Lammers, J. & Burgmer, P. 2019. Power increases the self-serving bias in the attribution of collective successes and failures. *European Journal of Social Psychology,* 49(5)**,** pp 1087-1095. https://doi.org/10.1002/ejsp.2556

Lane, D. C. 2004. Irrational agents or accomplished social actors? *Systems Research and Behavioral Science,* 21(4)**,** pp 433. https://www.proquest.com/scholarly-

© University of Pretoria

journals/irrational-agents-accomplished-social-actors/docview/196883526/se-2?accountid=14717
http://UnivofPretoria.on.worldcat.org/atoztitles/link?sid=ProQ:&issn=10927026&volume=21&issue=4&title=Systems+Research+and+Behavioral+Science&spage=433&date=2004-07-01&atitle=Irrational+agents+or+accomplished+social+actors%3F&au=Lane%2C+David+C&id=doi:

Lane, D. C. & Rouwette, E. A. 2022. Towards a behavioural system dynamics: exploring its scope and delineating its promise. *European Journal of Operational Research*. https://www.sciencedirect.com/science/article/pii/S0377221722006609

Lee, S. Application of AHP and fuzzy AHP to decision-making problems in construction. 52nd ASC annual international conference proceedings, 2016. 13-16. https://www.semanticscholar.org/paper/Application-of-AHP-and-Fuzzy-AHP-to-Decision-Making-Lee/2d599291480b818e7285cc115b514d82299f3118

Lefike, M. 2021. *A systems framework for analysing the impact of corporate social investment projects that focus on Information Technology.* PhD (Information Technology), University of Pretoria.

León, J. P. A. 2008. Systems Thinking: The Key for the Creation of Truly Desired Futures. *International Journal of Reality Therapy,* 28(1)**,** pp 15-20.

Leonard, T. C. & Richard H. Thaler, C. R. S. 2008. Nudge: Improving decisions about health, wealth, and happiness. Springer. https://books.google.co.za/books/about/Nudge.html?id=dSJQn8egXvUC&redir_esc=y

Levin, I. P., Schneider, S. L. & Gaeth, G. J. 1998. All frames are not created equal: A typology and critical analysis of framing effects. *Organizational behavior and human decision processes,* 76(2)**,** pp 149-188. https://doi.org/10.1006/obhd.1998.2804

Li, W., Jiang, R., Wu, H., Xie, J., Zhao, Y., Song, Y. & Li, F. 2023. A system dynamics model of urban rainstorm and flood resilience to achieve the sustainable development goals. *Sustainable Cities and Society,* 96(3-8.

Lin, B. & Yang, M. 2023. Choosing the right policy: Factors influencing the preferences of consumption-side personal carbon reduction policies. *Journal of Environmental Management,* 326(2-7.

Liu, Z., Schraven, D., de Jong, M. & Hertogh, M. 2023. The societal strength of transition: a critical review of the circular economy through the lens of inclusion. *International Journal of Sustainable Development & World Ecology,* 30(7)**,** pp 826-849. https://doi.org/10.1080/13504509.2023.2208547

© University of Pretoria

Lohr, S. 2000. Sampling: Design and Analysis. *Technometrics,* 42(73-116. http://dx.doi.org/10.2307/1271491

Lubowiecki-Vikuk, A., Dąbrowska, A. & Machnik, A. 2021. Responsible consumer and lifestyle: Sustainability insights. *Sustainable Production and Consumption,* 25(91-101. https://www.sciencedirect.com/science/article/pii/S2352550920304371

Luengo, D., Martino, L., Bugallo, M., Elvira, V. & Särkkä, S. 2020. A survey of Monte Carlo methods for parameter estimation. *EURASIP Journal on Advances in Signal Processing,* 2020(1-62.

Maani, K. E. & Maharaj, V. 2004. Links between systems thinking and complex decision making. *System Dynamics Review: The Journal of the System Dynamics Society,* 20(1)**,** pp 21-48.

Maceika, A., Bugajev, A., Šostak, O. R. & Vilutienė, T. 2021. Decision Tree and AHP Methods Application for Projects Assessment: A Case Study. *Sustainability,* 13(10)**,** pp 1-32. https://www.mdpi.com/2071-1050/13/10/5502

Mack, A. 2003. Inattentional Blindness:Looking Without Seeing. *Current Directions in Psychological Science,* 12(5)**,** pp 180-184. https://journals.sagepub.com/doi/abs/10.1111/1467-8721.01256

Maibach, E. 2019. Increasing public awareness and facilitating behavior change: Two guiding heuristics.

Mandl, C. E. 2023. Escalation: Dynamics of Mutual Distrust. *Managing Complexity in Social Systems: Leverage Points for Policy and Strategy.* Springer.

Mao, Y., Akyol, E. & Hovakimyan, N. 2021. Impact of Confirmation Bias on Competitive Information Spread in Social Networks. *IEEE Transactions on Control of Network Systems,* 8(2)**,** pp 816-827. https://doi.org/10.1109/TCNS.2021.3050117

March, S. T. & Smith, G. F. 1995. Design and natural science research on information technology. *Decision Support Systems,* 15(4)**,** pp 251-266. https://www.sciencedirect.com/science/article/pii/0167923694000412

Marcos-Merino, J. M., Corbacho-Cuello, I. & Hernández-Barco, M. 2020. Analysis of Sustainability Knowingness, Attitudes and Behavior of a Spanish Pre-Service Primary Teachers Sample. *Sustainability,* 12(18)**,** pp 7445. https://www.mdpi.com/2071-1050/12/18/7445

Mastria, S., Vezzil, A. & De Cesarei, A. 2023. Going Green: A Review on the Role of Motivation in Sustainable Behavior. *Sustainability,* 15(21)**,** pp 15429. https://www.mdpi.com/2071-1050/15/21/15429

Matthews, D. 2005. Pragmatism Meets Systems Thinking: The Legacy of C. West Churchman. https://link.springer.com/chapter/10.1007/0-387-27589-4_10

© University of Pretoria

Maule, A. J. & Maule, S. 2016. Aiding Lay Decision Making Using a Cognitive Competencies Approach. *Frontiers in Psychology,* 6(1-10. https://www.frontiersin.org/article/10.3389/fpsyg.2015.01884

McCausland, T. 2021. Innovating for Sustainability. *Research-Technology Management,* 64(4)**,** pp 59-63. https://doi.org/10.1080/08956308.2021.1924520

McDonough, W. & Braungart, M. 2002. *Cradle to Cradle: Remaking the Way We Make Things*: Farrar, Straus and Giroux. https://books.google.co.za/books/about/Cradle_to_Cradle.html?id=KFX5RprPGQ0C&redir_esc=y

McDonough, W., Braungart, M. & Clinton, B. 2013. *The Upcycle: Beyond Sustainability--Designing for Abundance*: Farrar, Straus and Giroux. https://books.google.co.za/books?id=tghQAoCWjvcC

Meadows, D., Randers, J., Meadows, D., Diamond, J. & Costanza, R. 2006. Limits to growth: The 30-year update. *Ecological Economics,* 59(3)**,** pp 397-399. http://dx.doi.org/10.1016/j.ecolecon.2005.10.008

Meadows, D. H., Meadows, D. L. & Randers, J. 1972. *The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind*: Universe Books. https://books.google.co.za/books?id=w_9dAAAAIAAJ

Meadows, D. H., Meadows, D. L. & Randers, J. 1992. *Beyond the limits : confronting global collapse, envisioning a sustainable future*, Post Mills, Vt.: Chelsea Green Pub. Co. http://www.gbv.de/dms/bowker/toc/9780930031558.pdf

Meadows, D. H. & Rome, C. o. 1974. *The Limits to growth : a report for the Club of Rome's project on the predicament of mankind*, London: Pan Books.

Mendoza, G. A. & Martins, H. 2006. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. *Forest ecology and management,* 230(1-3)**,** pp 1-22. https://doi.org/10.1016/j.foreco.2006.03.023

Michael Shayne, G., Giovanni, D. & Dan, L. 2007. Boom and Bust Behavior: On the Persistence of Strategic Decision Biases and their Collective Outcome, https://ideas.repec.org/p/ssa/lemwps/2007-13.html

Michaelis, B., Rogbeer, S., Schweizer, L. & Özleblebici, Z. 2021. Clarifying the boundary conditions of value creation within dynamic capabilities framework: a grafting approach. *Review of Managerial Science,* 15(6)**,** pp 1797-1820. https://doi.org/10.1007/s11846-020-00403-2

Michel, M. & Peters, M. A. K. 2020. Confirmation bias without rhyme or reason. *Synthese : An International Journal for Epistemology, Methodology and*

© University of Pretoria

Philosophy of Science, 199(1-2), pp 2757-2772. https://link.springer.com/article/10.1007/s11229-020-02910-x

Mikichurova, O. V. & Vlialko, I. V. 2021. Circular law as a legal basis for a circular economy. *IOP Conference Series: Earth and Environmental Science,* 915(1), pp 012022. http://dx.doi.org/10.1088/1755-1315/915/1/012022

Miles, M. B. & Huberman, A. M. 1994. *Qualitative data analysis: An expanded sourcebook, 2nd ed*, Thousand Oaks, CA, US: Sage Publications, Inc.

Milfont, T. L., Wilson, M. S. & Sibley, C. G. 2017. The public's belief in climate change and its human cause are increasing over time. *PLoS One,* 12(3), pp 1-5.

Milios, L. 2018. Advancing to a Circular Economy: three essential ingredients for a comprehensive policy mix. *Sustainability Science,* 13(3), pp 861-878. https://doi.org/10.1007/s11625-017-0502-9

Milkman, K. L., Chugh, D. & Bazerman, M. H. c. 2009. How Can Decision Making Be Improved? *Perspectives on Psychological Science,* 4(4), pp 379-383. http://dx.doi.org/10.1111/j.1745-6924.2009.01142.x

Miller, D. W. 1969. The Systems Approach (Review). *Management Science,* 16(4), pp 288-291. http://www.jstor.org/stable/2628806

Miller, T. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence,* 267(1-38. https://doi.org/10.1016/j.artint.2018.07.007

Moallemi, E. A., Hosseini, S., Eker, S., Gao, L., Bertone, E., Szetey, K. & Bryan, B. 2022. Eight archetypes of sustainable development goal (SDG) synergies and trade-offs. *Earth's Future,* 10(9), pp 1-21.

Montibeller, G. & Von Winterfeldt, D. 2015. Cognitive and motivational biases in decision and risk analysis. *Risk analysis,* 35(7), pp 1230-1251.

Morewedge, C. K. & Kahneman, D. 2010. Associative processes in intuitive judgment. *Trends in cognitive sciences,* 14(10), pp 435-440. https://pubmed.ncbi.nlm.nih.gov/20696611
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5378157/

Morewedge, C. K., Yoon, H., Scopelliti, I., Symborski, C. W., Korris, J. H. & Kassam, K. S. 2015. Debiasing decisions: Improved decision making with a single training intervention. *Policy Insights from the Behavioral and Brain Sciences,* 2(1), pp 129-140. https://doi.org/10.1177/2372732215600886

Morse, J. M., Barrett, M., Mayan, M., Olson, K. & Spiers, J. 2002. Verification Strategies for Establishing Reliability and Validity in Qualitative Research. *International Journal of Qualitative Methods,* 1(2), pp 13-22. https://journals.sagepub.com/doi/abs/10.1177/160940690200100202

© University of Pretoria

Mouad, L. & Zakia, B. 2023. Cognitive bias between individuals and groups: how to improve sustainable decision making? *African Scientific Journal,* 3(20)**,** pp 457-457.

Mussweiler, T. & Strack, F. 1999. Comparing is believing: A selective accessibility model of judgmental anchoring. *European review of social psychology,* 10(1)**,** pp 135-167. https://doi.org/10.1080/14792779943000044

Mutingi, M., Mbohwa, C. & Dube, P. 2017. System dynamics archetypes for capacity management of energy systems. *Energy Procedia,* 141(199-205. https://www.sciencedirect.com/science/article/pii/S1876610217354449

Nabavi, E., Daniell, K. A. & Najafi, H. 2017. Boundary matters: the potential of system dynamics to support sustainability? *Journal of Cleaner Production,* 140(312-323. https://www.sciencedirect.com/science/article/pii/S0959652616300993

Nadiia, R., Yusuf, I., Yaroslav, K.-S., Nataliia, B., Mykola, S. & Olha, B. Systems thinking to investigate the archetype of globalization. International Conference on Business and Technology, 2021. Springer, 123-140.

Naeem, M., Ozuem, W., Howell, K. & Ranfagni, S. 2023. A Step-by-Step Process of Thematic Analysis to Develop a Conceptual Model in Qualitative Research. *International Journal of Qualitative Methods,* 22(1-18. https://journals.sagepub.com/doi/abs/10.1177/16094069231205789

Naeem, M., Ozuem, W., Howell, K. & Ranfagni, S. 2024. Demystification and Actualisation of Data Saturation in Qualitative Research Through Thematic Analysis. *International Journal of Qualitative Methods,* 23(1-10. https://journals.sagepub.com/doi/abs/10.1177/16094069241229777

Naugle, A., Langarudi, S. & Clancy, T. 2024. What is (quantitative) system dynamics modeling? Defining characteristics and the opportunities they create. *System Dynamics Review,* 40(2)**,** pp 1-8. https://onlinelibrary.wiley.com/doi/abs/10.1002/sdr.1762

Nickerson, R. S. 1998. Confirmation bias: A ubiquitous phenomenon in many guises. *Review of general psychology,* 2(2)**,** pp 175-220.

Nikolaou, I. E., Jones, N. & Stefanakis, A. 2021. Circular Economy and Sustainability: the Past, the Present and the Future Directions. *Circular Economy and Sustainability,* 1(1)**,** pp 1-20. https://doi.org/10.1007/s43615-021-00030-3

Nowell, L., Norris, J., White, D. & Moules, N. 2017. Thematic Analysis: Striving to Meet the Trustworthiness Criteria. *International Journal of Qualitative,* 16(1-13.

OECD 2017. *Investing in Climate, Investing in Growth*: Organisation for Economic Co-operation and Development. https://www.oecd-ilibrary.org/content/publication/9789264273528-en

© University of Pretoria

Olabode, S. & Bakare, A. 2020. AN ASSESSMENT OF THE RELIABILITY OF SECONDARY DATA IN MANAGEMENT SCIENCE RESEARCH. *LASU Journal of Employment Relations & Human Resource Management,* 1(

Oosthuizen, R. 2014. *Modelling methodology for assessing the impact of new technology on complex sociotechnical systems.* University of Pretoria.

Oosthuizen, R. Application of System Archetypes to Improve System Dynamics Modelling. 9th ANNUAL SOUTH AFRICAN SYSTEM DYNAMICS CHAPTER CONFERENCE, 2021 Virtual, November 18-19, 2021. 1-11. https://www.researchgate.net/publication/358817617_Application_of_System_Archetypes_to_Improve_System_Dynamics_Modelling

Oschinsky, F. M., Stelter, A. & Niehaves, B. 2021. Cognitive biases in the digital age – How resolving the status quo bias enables public-sector employees to overcome restraint. *Government Information Quarterly,* 38(4)**,** pp 101611. https://www.sciencedirect.com/science/article/pii/S0740624X21000472

Osterwalder, A. & Pigneur, Y. 2010. *Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers*.

Palmucci, D. N. & Ferraris, A. 2023. Climate change inaction: Cognitive bias influencing managers' decision making on environmental sustainability choices. The role of empathy and morality with the need of an integrated and comprehensive perspective. *Frontiers in Psychology,* 14(1130059.

Pasman, H. J., Rogers, W. J. & Behie, S. W. 2022. Selecting a method/tool for risk-based decision making in complex situations. *Journal of Loss Prevention in the Process Industries,* 74(2-6. https://www.sciencedirect.com/science/article/pii/S0950423021002758

Pasmore, W., Winby, S., Mohrman, S. A. & Vanasse, R. 2019. Reflections: Sociotechnical Systems Design and Organization Change. *Journal of Change Management,* 19(2)**,** pp 67-85. https://doi.org/10.1080/14697017.2018.1553761

Peffers, K., Tuunanen, T., Gengler, C., Rossi, M., Hui, W., Virtanen, V. & Bragge, J. 2006. The design science research process: A model for producing and presenting information systems research. *Proceedings of First International Conference on Design Science Research in Information Systems and Technology DESRIST*.

Pensado, O. 2024. Statistical Models: Propagation of Uncertainty and Monte Carlo Modeling. *Bayesian Network Modeling of Corrosion.* Springer.

Penzenstadler, B., Duboc, L., Venters, C. C., Betz, S., Seyff, N., Wnuk, K., Chitchyan, R., Easterbrook, S. M. & Becker, C. 2018. Software Engineering for Sustainability: Find the Leverage Points! *IEEE Software,* 35(4)**,** pp 22-33.

© University of Pretoria

Petrie, D. A., Lindstrom, R. R. & Campbell, S. G. 2024. The impact of cognitive biases, mental models, and mindsets on leadership and change in the health system. *Healthcare Management Forum,* 37(3)**,** pp 121-127. https://journals.sagepub.com/doi/abs/10.1177/08404704231215750

Petty, M. D. 2009. Verification and validation. *Principles of modeling and simulation: A multidisciplinary approach,* 121-149. https://d1wqtxts1xzle7.cloudfront.net/109752754/9780470403563202312291-1-dyqujh-libre.pdf?1703869385=&response-content-disposition=inline%3B+filename%3DPrinciples_of_Modeling_and_Simulation.pdf&Expires=1730916069&Signature=M1k4oGOjBVqlbgaSh6~ZsR6HzxA1CS-ZXakM7hGz-rF57WdEw~BuEYIwuPI5ukOtuuTtuUirDo76z9Ujb7Oj~N4YQ0SHCdwoJRJoIWJ54XZNM3xqVltLPGdbc~bC6D16Ie4izVOC4S57ggwi8p-mgJLhosVciMWFeDgEF0MN-gysK9nrrQluH75lBmcu7~05I5AmXJ~5b1FPtUPiIsDx-WCS4iCevUtByG0sYoVZkBO2a~mnSIw4KyOtV3MIo~qyaJ0xnYejNpSZeBoPjqTwEqzsx6IoZ8BTgTiju4QXpegzQhzDBmSXgAEsuSUE5OWMBIDKjjZwFSSjotXQb3A3bw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA#page=126

Phillips-Wren, G., Power, D. J. & Mora, M. 2019. Cognitive bias, decision styles, and risk attitudes in decision making and DSS. *Journal of Decision Systems,* 28(2)**,** pp 63-66. https://doi.org/10.1080/12460125.2019.1646509

Piccarozzi, M., Silvestri, C., Aquilani, B. & Silvestri, L. 2022. Is this a new story of the 'Two Giants'? A systematic literature review of the relationship between industry 4.0, sustainability and its pillars. *Technological Forecasting & Social Change,* 177(

Pinto, J. T. M., Sverdrup, H.U. & Diemer, A. 2019. Integrating life cycle analysis into system dynamics: the case of steel in Europe. *Environmental Systems Research,* 8(15)**,** pp 1-21.

Plekhanov, D., Franke, H. & Netland, T. H. 2022. Digital transformation: A review and research agenda. *European Management Journal,* 2-19. https://www.sciencedirect.com/science/article/pii/S0263237322001219

Prentice, R. 2004. Teaching Ethics, Heuristics, and Biases. *Journal of Business Ethics Education,* 1(1)**,** pp 55-72. https://www.proquest.com/scholarly-journals/teaching-ethics-heuristics-biases/docview/884628944/se-2?accountid=14717
http://UnivofPretoria.on.worldcat.org/atoztitles/link?sid=ProQ:&issn=16495195&volume=1&issue=1&title=Journal+of+Business+Ethics+Education&spage=55&date=2004-01-01&atitle=Teaching+Ethics%2C+Heuristics%2C+and+Biases&au=Prentice%2C+Robert&id=doi:

Prieto-Sandoval, V., Jaca, C. & Ormazabal, M. 2018. Towards a consensus on the circular economy. *Journal of Cleaner Production,* 179(605-615. https://www.sciencedirect.com/science/article/pii/S0959652617332146

© University of Pretoria

Proudfoot, K. 2023. Inductive/Deductive Hybrid Thematic Analysis in Mixed Methods Research. *Journal of Mixed Methods Research,* 17(3)**,** pp 308-326. https://journals.sagepub.com/doi/abs/10.1177/15586898221126816

Qiong, Z., Christine, P., Julie, B. Z. & James, R. M. 2016. More than Target 6.3: A Systems Approach to Rethinking Sustainable Development Goals in a Resource-Scarce World. *Engineering* [Online], 2. Available: https://www.researchgate.net/publication/314137221_More_than_Target_63_A_Systems_Approach_to_Rethinking_Sustainable_Development_Goals_in_a_Resource-Scarce_World.

Qiu, Q., Wang, Y., Qiao, S., Liu, R., Bian, Z., Yao, T. & Nguyen, T. S. 2020. Does air pollution affect consumer online purchasing behavior? The effect of environmental psychology and evidence from China. *Journal of Cleaner Production,* 260(3-6. https://www.sciencedirect.com/science/article/pii/S0959652620308428

Rask, N. 2022. An intersectional reading of circular economy policies: towards just and sufficiency-driven sustainabilities. *Local Environment,* 1-17. https://doi.org/10.1080/13549839.2022.2040467

Raworth, K. 2017. Why it's time for Doughnut Economics. *IPPR Progressive Review,* 24(3)**,** pp 216-222.

Raychaudhuri, S. Introduction to monte carlo simulation. 2008 Winter simulation conference, 2008. IEEE, 91-100.

Redman, A. & Wiek, A. Competencies for advancing transformations towards sustainability. Frontiers in Education, 2021. Frontiers Media SA, 1-11.

Reike, D., Vermeulen, W. & Witjes, S. 2018. The circular economy: New or refurbished as CE 3.0?—Exploring controversies in the conceptualization of the circular economy through a focus on history and resource value retention options. *Resource Conservation Recycling,* 64(135-246.

Reynolds, M. & Holwell, S. 2020. Introducing systems approaches. *Systems approaches to making change: A practical guide,* 1-24.

Richardson, G. P. 2011. Reflections on the foundations of system dynamics. *System dynamics review,* 27(3)**,** pp 219-243.

Robertson, M. 2021. *Sustainability principles and practice*: Routledge.

Rocha, J., Malmborg, K., Gordon, L., Brauman, K. & DeClerck, F. 2020. Mapping social-ecological systems archetypes. *Environmental Research Letters,* 15(3)**,** pp 1-10.

Rockström, J., Gupta, J., Qin, D., Lade, S. J., Abrams, J. F., Andersen, L. S., Armstrong McKay, D. I., Bai, X., Bala, G., Bunn, S. E., Ciobanu, D., DeClerck,

© University of Pretoria

F., Ebi, K., Gifford, L., Gordon, C., Hasan, S., Kanie, N., Lenton, T. M., Loriani, S., Liverman, D. M., Mohamed, A., Nakicenovic, N., Obura, D., Ospina, D., Prodani, K., Rammelt, C., Sakschewski, B., Scholtens, J., Stewart-Koster, B., Tharammal, T., van Vuuren, D., Verburg, P. H., Winkelmann, R., Zimm, C., Bennett, E. M., Bringezu, S., Broadgate, W., Green, P. A., Huang, L., Jacobson, L., Ndehedehe, C., Pedde, S., Rocha, J., Scheffer, M., Schulte-Uebbing, L., de Vries, W., Xiao, C., Xu, C., Xu, X., Zafra-Calvo, N. & Zhang, X. 2023. Safe and just Earth system boundaries. *Nature,* 619(7968)**,** pp 102-111. https://doi.org/10.1038/s41586-023-06083-8

Roese, N. J. & Vohs, K. D. 2012. Hindsight bias. *Perspectives on psychological science,* 7(5)**,** pp 411-426.

Rondoni, A. & Grasso, S. 2021. Consumers behaviour towards carbon footprint labels on food: A review of the literature and discussion of industry implications. *Journal of Cleaner Production,* 301(5-25.

Roos, M. 2024. Feedback, Circular Causality, and System Dynamics. *Principles of Complexity Economics: Concepts, Methods and Applications.* Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-51436-4_7

Rugen, P. & Callahan, B. 1996. An overview of Monte Carlo, a fifty year perspective. *Human and Ecological Risk Assessment: An International Journal,* 2(4)**,** pp 671-680.

Ruth, M. & Hannon, B. 2012. System Boundaries in Space and Time.

Ruzzier, C. A. & Woo, M. D. 2023. Discrimination with inaccurate beliefs and confirmation bias. *Journal of Economic Behavior and Organization,* 210(379-390.

Rykiel, E. 1996. Testing ecological models: The meaning of validation. *Ecological Modelling,* 90(229-244.

Saaty, T. L. 1990. HOW TO MAKE A DECISION - THE ANALYTIC HIERARCHY PROCESS. *European Journal of Operational Research,* 48(1)**,** pp 9-26. <Go to ISI>://WOS:A1990EG63900003

Saaty, T. L. 2005. Making and validating complex decisions with the AHP/ANP. *Journal of Systems Science and Systems Engineering,* 14(1)**,** pp 1-36.

Sagar, S. 2023. *Innovation and Sustainability in Business: Navigating the Future Landscape*.

Sajjad, A., Eweje, G. & Raziq, M. M. 2024. Sustainability leadership: An integrative review and conceptual synthesis. *Business Strategy and the Environment,* 33(4)**,** pp 2849-2867. https://onlinelibrary.wiley.com/doi/abs/10.1002/bse.3631

© University of Pretoria

Salvioni, D. M. & Almici, A. 2020. Transitioning Toward a Circular Economy: The Impact of Stakeholder Engagement on Sustainability Culture. *Sustainability,* 12(20)**,** pp 1-29. https://www.mdpi.com/2071-1050/12/20/8641

Samuelson, W. & Zeckhauser, R. 1988. Status quo bias in decision making. *Journal of risk and uncertainty,* 1(7-59.

Sandberg, M. 2021. Sufficiency transitions: A review of consumption changes for environmental sustainability. *Journal of Cleaner Production,* 293(2-15.

Sandfreni, S. & Adikara, F. 2020. *The Implementation of Soft System Methodology (SSM) for Systems Development in Organizations (Study Case: The Development of Tourism Information System in Palembang City)*.

Sargent, R. 2011. *Verification and validation of simulation models*.

Saryazdi, R., Bak, K. & Campos, J. L. 2019. Inattentional Blindness During Driving in Younger and Older Adults. *Frontiers in Psychology,* 10(https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00880

Sassanelli, C., Rosa, P., Rocca, R. & Terzi, S. 2019. Circular economy performance assessment methods: A systematic literature review. *Journal of Cleaner Production,* 229(440-453.

Savaget, P., Geissdoerfer, M., Kharrazi, A. & Evans, S. 2019. The theoretical foundations of sociotechnical systems change for sustainability: A systematic literature review. *Journal of Cleaner Production,* 206(878-892. https://www.sciencedirect.com/science/article/pii/S095965261832941X

Schismenos, S., Stevens, G. J., Emmanouloudis, D., Georgeou, N., Shrestha, S. & Katopodes, N. D. 2022. Using off-grid hydropower for community-led flood resilience: An integrated systems approach. *International Journal of Sustainable Energy,* 41(6)**,** pp 594-608.

Schoormann, T., Möller, F., Di Maria, M. & Große, N. 2023. Guiding Design Principle Projects: A Canvas for Young Design Science Researchers. *Journal of Information Systems Education,* 34(3)**,** pp 307-325.

Schot, J. & Kanger, L. 2018. Deep transitions: Emergence, acceleration, stabilization and directionality. *Research Policy,* 47(6)**,** pp 1045-1059. https://www.sciencedirect.com/science/article/pii/S0048733318300593

Schröder, P., Anggraeni, K. & Weber, U. 2018. The Relevance of Circular Economy Practices to the Sustainable Development Goals. *Journal of Industrial Ecology,* 23(

Schröder, P., Lemille, A. & Desmond, P. 2020. Making the circular economy work for human development. *Conservation and Recycling,* 156(1-9.

© University of Pretoria

Schulze Spüntrup, F., Ave, G. D., Imsland, L. & Harjunkoski, I. 2021. Integration of maintenance scheduling and planning for large-scale asset fleets. *Optimization and Engineering,* 4-28. https://doi.org/10.1007/s11081-021-09647-7

Scribante, N. P. 2019. *AN INVESTIGATION INTO REQUIREMENTS VOLATILITY USING SYSTEMS DYNAMICS MODELLING – THE DESIGN OF A REQUIREMENTS ENGINEERING RESEARCH TOOL.* PHILOSOPHIAE DOCTOR, UNIVERSITY OF PRETORIA.

Senge, P. 2006. *The Fifth Discipline: The art and practice of the learning organization*, London: Random House Books.

Seniuk, H. A., Cihon, T. M., Benson, M. & Luke, M. M. 2019. Making a Footprint in Environmental Sustainability: A Behavioral Systems Approach to Engaging the Behavioral Community. *Perspect Behav Sci,* 42(4)**,** pp 911-926.

Shama, M. S., Alharthi, A. S., Almulhim, F. A., Gemeay, A. M., Meraou, M. A., Mustafa, M. S., Hussam, E. & Aljohani, H. M. 2023. Modified generalized Weibull distribution: theory and applications. *Scientific Reports,* 13(1)**,** pp 1-16. https://doi.org/10.1038/s41598-023-38942-9

Sharifi, A., Allam, Z., Bibri, S. E. & Khavarian-Garmsir, A. R. 2024. Smart cities and sustainable development goals (SDGs): A systematic literature review of co-benefits and trade-offs. *Cities,* 146(1-15.

Sharma, D., Sridhar, S. & Claudio, D. 2020. Comparison of AHP-TOPSIS and AHP-AHP methods in multi-criteria decision-making problems. *International Journal of Industrial and Systems Engineering,* 34(203.

Sharot, T. 2011. The optimism bias. *Current biology,* 21(23)**,** pp 941-945.

Sharpe, B. 2020. Three Horizons The Patterning of Hope. Second edition. ed. Axminster: Triarchy Press.

Sheng, X., Zhang, X. & Zhou, X. 2023. Show me the impact: Communicating "behavioral impact message" to promote pro-environmental consumer behavior. *Sustainable Production and Consumption,* 35(709-723. https://www.sciencedirect.com/science/article/pii/S2352550922003335

Shu, L. L. & Bazerman, M. H. 2010. Cognitive barriers to environmental action: Problems and solutions. *Harvard Business School NOM Unit Working Paper,* 11-046)**,** pp.

Singh, P. & Giacosa, E. 2019. Cognitive biases of consumers as barriers in transition towards circular economy. *Management decision,* 921-937.

Singh, S., Upadhyay, S. P. & Powar, S. 2022. Developing an integrated social, economic, environmental, and technical analysis model for sustainable development using hybrid multi-criteria decision making methods. *Applied*

© University of Pretoria

Energy, 308(118235), pp 2-13. https://www.sciencedirect.com/science/article/pii/S0306261921014999

Singh, V. K., Singh, P., Karmakar, M., Leta, J. & Mayr, P. 2021. The journal coverage of Web of Science, Scopus and Dimensions: A comparative analysis. *Scientometrics,* 126(5113-5142.

Siva Muthuprakash, K. M. & Damani, O. P. 2017. A Stock and Flow Based Framework to Identify Indicators for a Holistic Comparison of Farming Practices. *Agricultural Research,* 6(3), pp 248-258. https://doi.org/10.1007/s40003-017-0266-6

Skene, K. & Murray, A. 2015. *Sustainable economics: context,challenges and opportunities for the 21 century practitioner.*, Sheffield: Greenfield. https://www.researchgate.net/publication/331212061_Sustainable_Economics_Context_Challenges_and_Opportunities_for_the_21st-Century_Practitioner

Slovic, P., Finucane, M. L., Peters, E. & MacGregor, D. G. 2007. The affect heuristic. *European Journal of Operational Research,* 177(3), pp 1333-1352. https://www.sciencedirect.com/science/article/pii/S0377221705003577

Solso, R. L., MacLin, M. K. & MacLin, O. H. 2005. *Cognitive psychology*: Pearson Education New Zealand.

Sondh, S., Upadhyay, D. S., Patel, S. & Patel, R. N. 2024. Strategic approach towards sustainability by promoting circular economy-based municipal solid waste management system- A review. *Sustainable Chemistry and Pharmacy,* 37(101337. https://www.sciencedirect.com/science/article/pii/S2352554123003716

Soosalu, G., Henwood, S. & Deo, A. 2019. Head, Heart, and Gut in Decision Making: Development of a Multiple Brain Preference Questionnaire. *SAGE Open,* 9(1), pp 2-15. https://journals.sagepub.com/doi/abs/10.1177/2158244019837439

Stahel, W. R. 2016. The circular economy. *Nature,* 531(7595), pp 435-438. https://doi.org/10.1038/531435a

Stanton, N. A. 2022. Systems-thinking for safety: a short introduction to the theory and practice of systems-thinking. *Ergonomics,* 65(2), pp 327-327. https://doi.org/10.1080/00140139.2021.1992965

Steffen, W., Richardson, K., Rockstrom, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B. & Sorlin, S. 2015. Planetary boundaries: Guiding human development on a changing planet. *Science,* 347(6223), pp 11. <Go to ISI>://WOS:000349221300039

Steiber, B.-G. Systems Engineering for a Circular Economy. 2016. INCOSE International Symposium, 190-204.

© University of Pretoria

Sterman, J. 2000. *Business dynamics : systems thinking and modeling for a complex world*, Boston: Irwin/McGraw-Hill. http://swbplus.bsz-bw.de/bsz089332229inh.pdf
http://swbplus.bsz-bw.de/bsz089332229inh.htm
http://bvbr.bib-bvb.de:8991/F?func=service&doc_library=BVB01&doc_number=009195995&line_number=0002&func_code=DB_RECORDS&service_type=MEDIA

Sterman, J. 2002. System Dynamics: systems thinking and modeling for a complex world.

Stirling, A. 2008. “Opening up” and “closing down” power, participation, and pluralism in the social appraisal of technology. *Science, Technology, & Human Values,* 33(2)**,** pp 262-294.

Štofková, J., Krejnus, M., Stofkova, K., Malega, P. & Binasova, V. 2022. *Use of the Analytic Hierarchy Process and Selected Methods in the Managerial Decision-Making Process in the Context of Sustainable Development*.

Struben, J. & Sterman, J. D. 2008. Transition challenges for alternative fuel vehicle and transportation systems. *Environment and Planning B: Planning and Design,* 35(6)**,** pp 1070-1097.

Sverko Grdic, Z., Krstinic Nizic, M. & Rudan, E. 2020. Circular economy concept in the context of economic development in EU countries. *Sustainability,* 12(7)**,** pp 3060.

Tavana, M., Soltanifar, M. & Santos-Arteaga, F. J. 2023. Analytical hierarchy process: revolution and evolution. *Annals of Operations Research,* 326(2)**,** pp 879-907. https://doi.org/10.1007/s10479-021-04432-2

Teimouri, M., Hoseini, S. M. & Nadarajah, S. 2013. Comparison of estimation methods for the Weibull distribution. *Statistics,* 47(1)**,** pp 93-109.

Tian, Z., Hou, P., Zhang, H., Si, S. & Cai, Z. Parameter Estimation of Mixed Weibull Distribution Based on Genetic Algorithm and Gradient Descent Method. 2021 Global Reliability and Prognostics and Health Management (PHM-Nanjing), 15-17 Oct. 2021 2021. 1-6.

Timóteo, T. R., Cazeri, G. T., Moraes, G. H. S. M. d., Sigahi, T. F. A. C., Zanon, L. G., Rampasso, I. S. & Anholon, R. 2024. Use of AHP and grey fixed weight clustering to assess the maturity level of strategic communication management in Brazilian startups. *Grey Systems: Theory and Application,* 14(1)**,** pp 69-90. https://doi.org/10.1108/GS-06-2023-0052

Toșa, C., Paneru, C. P., Joudavi, A. & Tarigan, A. K. M. 2024. Digital transformation, incentives, and pro-environmental behaviour: Assessing the uptake of sustainability in companies' transition towards circular economy. *Sustainable Production and Consumption*. https://www.sciencedirect.com/science/article/pii/S2352550924001295

© University of Pretoria

Trainer, T. & Alexander, S. 2019. The simpler way: envisioning a sustainable society in an age of limits. *real-world economics review,* 87(247-60.

Triantafyllidou, E. & Zabaniotou, A. 2022. From Theory to Praxis: 'Go Sustainable Living' Survey for Exploring Individuals Consciousness Level of Decision-Making and Action-Taking in Daily Life Towards a Green Citizenship. *Circular Economy and Sustainability,* 2(1)**,** pp 113-139. https://doi.org/10.1007/s43615-021-00046-9

Trist, E. L. & Bamforth, K. W. 1951. Some social and psychological consequences of the longwall method of coal-getting: An examination of the psychological situation and defences of a work group in relation to the social structure and technological content of the work system. *Human relations,* 4(1)**,** pp 3-38.

Tversky, A. & Kahneman, D. 1974. Judgment under Uncertainty: Heuristics and Biases. *Science,* 185(4157)**,** pp 1124-31.

Tversky, A. & Kahneman, D. 1974. Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science,* 185(4157)**,** pp 1124-1131.

Udeagha, M. C. & Muchapondwa, E. 2023. Environmental sustainability in South Africa: Understanding the criticality of economic policy uncertainty, fiscal decentralization, and green innovation. *Sustainable Development,* 31(3)**,** pp 1638-1651. https://onlinelibrary.wiley.com/doi/abs/10.1002/sd.2473

Uehara, T., Nagase, Y. & Wakeland, W. 2021. System Dynamics Modeling of Ecological–Economic Systems. *In:* Cavana, R. Y., Dangerfield, B. C., Pavlov, O. V., Radzicki, M. J. & Wheat, I. D. (eds.) *Feedback Economics: Economic Modeling with System Dynamics.* Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-67190-7_11

Ulrich, W. & Reynolds, M. 2020. Critical Systems Heuristics: The Idea and Practice of Boundary Critique. *In:* Reynolds, M. & Holwell, S. (eds.) *Systems Approaches to Making Change: A Practical Guide.* London: Springer London. https://doi.org/10.1007/978-1-4471-7472-1_6

United Nations Department of Economic and Social Affairs, U.-D. 2022. World Economic Situation and Prospects 2022,

Valverde, J., Aviles Palacios, C., Oliveira, C. & Renna, P. 2021. Circular Economy as a Catalyst for Progress towards the Sustainable Development Goals: A Positive Relationship between Two Self-Sufficient Variables. *Sustainability,* 13(22)(12652.

van der Linde, L. & Benade, S. Circular human sphere–The conceptual development of embedding a social pillar in the Circular Economy framework. EMEA WSEC 2023, 2023. 2-14. https://www.researchgate.net/profile/Leandi-Van-Der-Linde/publication/371226597_Circular_human_sphere_-

© University of Pretoria

The_conceptual_development_of_embedding_a_social_pillar_in_the_Circular_Economy_framework/links/6479b03679a7223765085050/Circular-human-sphere-The-conceptual-development-of-embedding-a-social-pillar-in-the-Circular-Economy-framework.pdf

van der Linde, L., Pretorius, L. & Oosthuizen, R. A systems approach to understanding cognitive bias in-fluences on stakeholders in the Circular Economy. INCOSE SA, 2022. 2-11. https://www.researchgate.net/profile/Leandi-Van-Der-Linde/publication/371226638_A_systems_approach_to_understanding_cognitive_bias_influences_on_stakeholders_in_the_Circular_Economy/links/6479ae2d79a7223765082f55/A-systems-approach-to-understanding-cognitive-bias-influences-on-stakeholders-in-the-Circular-Economy.pdf

van der Linde, L., Pretorius, L. & Oosthuizen, R. Behavioural System Dynamics: Conceptual Integration of Critical Bias Variables into Circular Economy Stakeholder Phases. 2023 Portland International Conference on Management of Engineering and Technology (PICMET), 2023. IEEE, 1-11.

van der Linde, L., Pretorius, L. & Oosthuizen, R. Can Behavioural System Dynamics Uncover Biases in the Circular Economy? South African System Dynamics Conference, November 16-17, 2023 2023 Johannesburg- South Africa. SASD Chapter, 5-18. https://www.researchgate.net/publication/380374003_Can_Behavioural_System_Dynamics_Uncover_Biases_in_the_Circular_Economy

van der Linde, L., Pretorius, L. & Oosthuizen, R. 2023. Validating A Behavioural System Dynamic Model To Investigate Bias, Decision-Making Influences In The Circular Economy. *International Conference on Industrial Engineering, Systems Engineering and Engineering Management (ISEM 2023)*.

van der Linde, L., Pretorius, L. & Oosthuizen, R. Sustainable Technology Management: A Causal Loop Analysis of Circular Economy Adoption and Stakeholder Dynamics. Portland International Conference on Management of Engineering and Technology (PICMET), 2024. IEEE, 1-10.

Van der Vorst, J. 2000. Effective food supply chains; generating, modelling and evaluating supply chain scenarios. *Wageningen Universiteit. Promotor: prof.ir. A.J.M. Beulens n prof.dr. P. van Beek. - Wageningen : Vorst, 2000. - ISBN 90 5808 26 -X,* 305.

Van Dyk, D. J. & Pretorius, L. 2014. A systems thinking approach to the sustainability of quality improvement programmes. *South African Journal of Industrial Engineering,* 25(1)**,** pp 71-84.

Vanhuyse, F., Fejzić, E., Ddiba, D. & Henrysson, M. 2021. The lack of social impact considerations in transitioning towards urban circular economies: a scoping review. *Sustainable Cities and Society,* 75(2-8. https://www.sciencedirect.com/science/article/pii/S2210670721006673

© University of Pretoria

Vanson, G., Marangé, P. & Levrat, E. 2022. End-of-Life Decision making in circular economy using generalized colored stochastic Petri nets. *Autonomous Intelligent Systems,* 2(1)**,** pp 3-22. https://doi.org/10.1007/s43684-022-00022-6

Velter, M. G. E., Bitzer, V., Bocken, N. M. P. & Kemp, R. 2020. Sustainable business model innovation: The role of boundary work for multi-stakeholder alignment. *Journal of Cleaner Production,* 247(2-7. https://www.sciencedirect.com/science/article/pii/S0959652619343677

Venable, J., Pries-Heje, J. & Baskerville, R. 2016. FEDS: a Framework for Evaluation in Design Science Research. *European Journal of Information Systems,* 25(1)**,** pp 77-89. <Go to ISI>://WOS:000370469600006

Vennix, J. A. 1999. Group model-building: tackling messy problems. *System Dynamics Review: The Journal of the System Dynamics Society,* 15(4)**,** pp 379-401.

Vighnesh, N. V., Balachandra, P., Chandrashekar, D. & Sawang, S. 2023. How cultural values influence sustainable consumption behavior? An empirical investigation in a non-Western context. *Sustainable Development,* 31(2)**,** pp 990-1007. https://onlinelibrary.wiley.com/doi/abs/10.1002/sd.2436

Vila, R. & Niyazi Çankaya, M. 2022. A bimodal Weibull distribution: properties and inference. *Journal of Applied Statistics,* 49(12)**,** pp 3044-3062. https://doi.org/10.1080/02664763.2021.1931822

Visser, W. & Crane, A. 2010. Corporate Sustainability and the Individual: Understanding What Drives Sustainability Professionals as Change Agents. *SSRN Electronic Journal,* 5-32. https://www.researchgate.net/publication/228202329_Corporate_Sustainability_and_the_Individual_Understanding_What_Drives_Sustainability_Professionals_as_Change_Agents

Walsh, I. & Rowe, F. 2023. BIBGT: combining bibliometrics and grounded theory to conduct a literature review. *European Journal of Information Systems,* 32(4)**,** pp 653-674. https://doi.org/10.1080/0960085X.2022.2039563

Walwyn, D. R. Influence of personal epistemology on research method: implications for research education. 8th Research in Engineering Education Symposium (REES 2019), 2019. 56-63.

Wan, G., Dawod, A. Y., Chanaim, S. & Ramasamy, S. S. 2023. Hotspots and trends of environmental, social and governance (ESG) research: A bibliometric analysis. *Data Science and Management,* 6(2)**,** pp 65-75.

Wang, H. & Zhang, D. 2023. Examining the interplay between fossil fuel mining, sustainable growth, and economic prosperity. *Resources Policy,* 87(104-324. https://www.sciencedirect.com/science/article/pii/S0301420723010358

Warrick, D. D. 2023. Revisiting resistance to change and how to manage it: What has been learned and what organizations need to do. *Business Horizons,* 66(4)**,** pp

© University of Pretoria

433-441. https://www.sciencedirect.com/science/article/pii/S0007681322001070

Warwick, J. 2008. A Case Study Using Soft Systems Methodology in the Evolution of a Mathematics Module. *The Mathematics Enthusiast*.

Watkins, J. A. 2000. *A structured systems approach to model conceptualization : an executive management perspective.* Thesis (PhD (Industrial Systems)) PhD.

Westra, S. & Zscheischler, J. 2023. Accounting for systemic complexity in the assessment of climate risk. *One Earth,* 6(6)**,** pp 645-655. https://doi.org/10.1016/j.oneear.2023.05.005

Whitmarsh, L., Poortinga, W. & Capstick, S. 2021. Behaviour change to address climate change. *Current Opinion in Psychology,* 42(76-81. https://www.sciencedirect.com/science/article/pii/S2352250X21000427

Wiedmann, T. O., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J. & Kanemoto, K. 2015. The material footprint of nations. *Proceedings of the National Academy of Sciences,* 112(20)**,** pp 6271. http://www.pnas.org/content/112/20/6271.abstract

Wiers, R. W., Zerhouni, O., Uyl, T. d. & Boffo, M. 2020. Chapter 17 - Cognitive bias modification in the treatment of addiction. *In:* Verdejo-Garcia, A. (ed.) *Cognition and Addiction.* Academic Press. https://www.sciencedirect.com/science/article/pii/B9780128152980000174

Wilke, A. & Mata, R. 2012. Cognitive Bias. *In:* Ramachandran, V. S. (ed.) *Encyclopedia of Human Behavior (Second Edition).* San Diego: Academic Press. https://www.sciencedirect.com/science/article/pii/B978012375000600094X

Williams, A., Kennedy, S., Philipp, F. & Whiteman, G. 2017. Systems thinking: A review of sustainability management research. *Journal of Cleaner Production,* 148(866-881. https://www.sciencedirect.com/science/article/pii/S0959652617302068

Willits, F. K., Theodori, G. L. & Luloff, A. 2016. Another look at Likert scales. *Journal of Rural Social Sciences,* 31(3)**,** pp 126-139.

Wind, Y. & Saaty, T. L. 1980. Marketing applications of the analytic hierarchy process. *Management science,* 26(7)**,** pp 641-658.

Winterich, K. P., Reczek, R. W. & Makov, T. 2023. How lack of knowledge on emissions and psychological biases deter consumers from taking effective action to mitigate climate change. *Journal of the Academy of Marketing Science,* 2-9. https://doi.org/10.1007/s11747-023-00981-z

Wolstenholme, E. 2004. Using generic system archetypes to support thinking and modelling. *System Dynamics Review,* 20(4)**,** pp 341-356. https://onlinelibrary.wiley.com/doi/abs/10.1002/sdr.302

© University of Pretoria

Wonneberger, A., Meijers, M. H. C. & Schuck, A. R. T. 2020. Shifting public engagement: How media coverage of climate change conferences affects climate change audience segments. *Public Underst Sci,* 29(2)**,** pp 176-193.

Wuyts, W. & Marin, J. 2022. "Nobody" matters in circular landscapes. *Local Environment,* 1-18. https://doi.org/10.1080/13549839.2022.2040465

Yang, L. & Cormican, K. 2021. The Crossovers and Connectivity between Systems Engineering and the Sustainable Development Goals: A Scoping Study. Sustainability 2021, 13, 3176. *Systems Engineering for Sustainable Development Goals,* 81.

Yasseri, T. & Reher, J. 2022. Fooled by facts: quantifying anchoring bias through a large-scale experiment. *Journal of Computational Social Science,* 5(1)**,** pp 1001-1021.

Yousof, H. M., Goual, H., Emam, W., Tashkandy, Y., Alizadeh, M., Ali, M. M. & Ibrahim, M. 2023. An Alternative Model for Describing the Reliability Data: Applications, Assessment, and Goodness-of-Fit Validation Testing. *Mathematics,* 11(6)**,** pp 1308. https://www.mdpi.com/2227-7390/11/6/1308

Zanghelini, G. M., Cherubini, E. & Soares, S. R. 2018. How Multi-Criteria Decision Analysis (MCDA) is aiding Life Cycle Assessment (LCA) in results interpretation. *Journal of Cleaner Production,* 172(609-622.

Zavos, S., Lehtokunnas, T. & Pyyhtinen, O. 2024. The (missing) social aspect of the circular economy: a review of social scientific articles. *Sustainable Earth Reviews,* 7(1)**,** pp 11. https://doi.org/10.1186/s42055-024-00083-w

Zhang, Y., Pan, Z., Li, K. & Guo, Y. 2018. Self-Serving Bias in Memories. *Experimental psychology,* 65(4)**,** pp 236-244.

Zhao, H., Fu, S. & Chen, X. 2020. Promoting users' intention to share online health articles on social media: The role of confirmation bias. *Information Processing and Management,* 57(6)**,** pp.

Zhao, H., Zhao, H. & Guo, S. 2017. Evaluating the comprehensive benefit of eco-industrial parks by employing multi-criteria decision making approach for circular economy. *Journal of Cleaner Production,* 142(2262-2276. https://www.sciencedirect.com/science/article/pii/S0959652616318807

Zlaugotne, B., Zihare, L., Balode, L., Kalnbalkite, A., Khabdullin, A. & Blumberga, D. 2020. Multi-Criteria Decision Analysis Methods Comparison. *Environmental and Climate Technologies,* 24(1)**,** pp 454-471. https://doi.org/10.2478/rtuect-2020-0028

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1. Appendix A – Ethics approval

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Faculty of Engineering, Built Environment and Information Technology

Fakulteit Ingenieurswese, Bou-omgewing en Inligtingtegnologie / Lefapha la Boetšenere, Tikologo ya Kago le Theknolotši ya Tshedimošo

2 May 2023

Reference number: EBIT/21/2023

Miss L van der Linde
Department: Engineering and Technology Management
University of Pretoria
Pretoria
0083

Dear Miss L van der Linde,

FACULTY COMMITTEE FOR RESEARCH ETHICS AND INTEGRITY

Your recent application to the EBIT Research Ethics Committee refers.

Approval is granted for the application with reference number that appears above.

1. This means that the research project entitled "A systems approach to cognitive bias influences on stakeholders in the Circular Economy" has been approved as submitted. It is important to note what approval implies. This is expanded on in the points that follow.
2. This approval does not imply that the researcher, student or lecturer is relieved of any accountability in terms of the Code of Ethics for Scholarly Activities of the University of Pretoria, or the Policy and Procedures for Responsible Research of the University of Pretoria. These documents are available on the website of the EBIT Research Ethics Committee.
3. If action is taken beyond the approved application, approval is withdrawn automatically.
4. According to the regulations, any relevant problem arising from the study or research methodology as well as any amendments or changes, must be brought to the attention of the EBIT Research Ethics Office.
5. The Committee must be notified on completion of the project.

The Committee wishes you every success with the research project.

Kai-Yin

Prof K.-Y. Chan
Chair: Faculty Committee for Research Ethics and Integrity
FACULTY OF ENGINEERING, BUILT ENVIRONMENT AND INFORMATION TECHNOLOGY

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2. Appendix B – Survey questions extracted from Jotform

https://form.jotform.com/u20563991/research-survey-questionnaire

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Research Survey Questionnaire

Thank you for taking the time to answer these questions. Providing feedback is a valuable contribution to the research process, and the researcher appreciate your contribution. See definitions for terms at the end of the survey.

Study Title

A SYSTEMS APPROACH TO COGNITIVE BIAS INFLUENCES ON STAKEHOLDERS IN THE CIRCULAR ECONOMY

By selecting the "Yes" option I hereby voluntarily grant my permission for participation in this anonymous survey. I understand my right to choose whether to participate in the research project and that the information provided will be handled confidentially. I am aware that the results of the survey may be used for academic publication. *

- ◯ Yes
- ◯ No

1. What is your job title? *

This question is to identify specific stakeholders in the Circular Economy

2. Do you believe sustainability should be focused on? *

- ◯ Yes
- ◯ No

3. Where do you think will be the most important place to adopt a more sustainable means? *

- ☐ Personal lifestyle
- ☐ Product manufacturing
- ☐ Mining
- ☐ Farming
- ☐ Food industry

4. Which items do you recycle, repair or re-use in your personal life? *

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This question is for Circular Economy phase identification to implement better decision-making

5. Which items do you recycle, repair or re-use in your professional life? *

This question is for Circular Economy phase identification to implement better decision-making

6. Which of the following factors will convince you to buy/use sustainable products? *

- [ ] Green information availability on labels
- [ ] Green information accuracy on labels
- [ ] Reduced cost
- [ ] Re-usability
- [ ] Better quality

7. Are you willing to change your habits to be more sustainable? *

- ( ) Yes
- ( ) No

8. Do you think that the benefits of economic growth and development should outweigh the costs to the environment? *

- ( ) Yes
- ( ) No

9. Do you believe that governments should take a more active role in promoting sustainability, even if it means limiting individual freedom of choice or imposing strict regulations? *

- ( ) Yes
- ( ) No

10. How do you respond to information or media that challenges your views on sustainability and the environment? *

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This question is to identify the availability cognitive bias

11. Please select the options below that best represent your answer for each statement *

	Very poor	Poor	Average	Good	Excellent
How informed are you about sustainability issues?	○	○	○	○	○
How confident are you in your ability to make environmentally friendly choices in your daily life?	○	○	○	○	○

12. Please select the options below that best represent your answer for each statement *

	Very unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Very likely
Would you spend more money to buy repaired, re-used or recycled products than new ones?	○	○	○	○	○
How willing are you to make changes to your lifestyle or consumption habits in order to support sustainability and protect the environment?	○	○	○	○	○
How much do you believe that cognitive biases can impact the success or failure of circular economy initiatives?	○	○	○	○	○

13. Please select the options below that best represent your answer for each statement *

	Never	Rarely	Sometimes	Often	Always
How often do you make an effort to reduce your carbon footprint or limit your use of single-use plastics?	○	○	○	○	○

14. Please select the options below that best represent your answer for each statement *

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
Do you agree with the following view: Is it imperative to reduce the use of fossil fuels in our daily lives, by increasing the demand for sustainable products?	○	○	○	○	○
Do you agree that it is important that society follows environmentally friendly practices?	○	○	○	○	○
Do you agree with the following view: There is no proper manner to change the awareness of the public for the establishment of a more sustainable reality?	○	○	○	○	○
Do you think it is important for individuals to					

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To what extent do you believe that environmental problems can be solved through technology and innovation?	○	○	○	○	○
To what extent do you believe that businesses should prioritize sustainability in their decision-making?	○	○	○	○	○
To what extent do you think that climate change is caused by human activity?	○	○	○	○	○
To what extent do you believe that cognitive biases influence decision-making in the adoption of circular economy principles and practices?	○	○	○	○	○
To what extent do you think that cognitive biases play a role in the resistance to change and adoption of circular economy practices?	○	○	○	○	○

Definitions of terms:

1. Sustainability: Sustainability is the ability of an entity or system to maintain its balance and function over time while preserving the natural environment and resources for future generations. It is an approach that seeks to balance economic, social, and environmental factors to meet the needs of the present without compromising the ability of future generations to meet their own needs.

2. Systems Engineering: Systems engineering is an interdisciplinary approach that focuses on the design, development, and implementation of complex systems. It involves the integration of multiple disciplines, including engineering, mathematics, computer science, and management, to ensure that the system operates effectively and efficiently.

3. Cognitive Biases: Cognitive biases are systematic errors in thinking and decision-making that occur when people rely on mental shortcuts, heuristics, or previous experiences rather than careful reasoning or analysis. These biases can lead to flawed judgments, inaccurate conclusions, and irrational behaviors, and can affect areas such as perception, memory, attention, and decision-making.

4. Circular Economy: The circular economy is an economic concept that seeks to promote sustainability and reduce waste by closing the loop of resource use. The traditional linear economy model of "take, make, use, and dispose" is replaced by a closed-loop system where materials and resources are kept in use for as long as possible.

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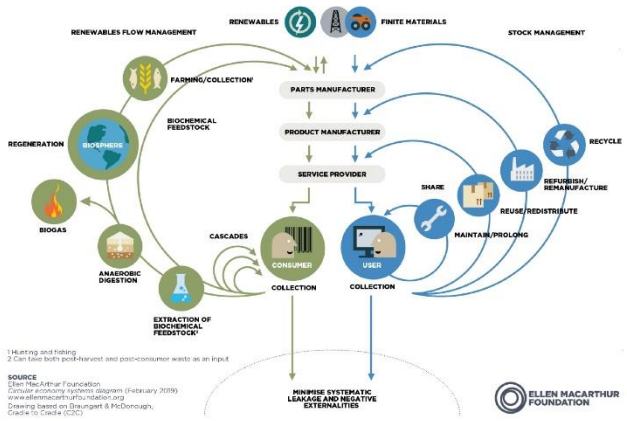

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STRICTLY CONFIDENTIAL

Researcher: Leandi van der Linde; Contact details: u20563991@tuks.co.za. In partial fulfilment of the requirements for the degree of PHILOSOPHIAE DOCTOR - Engineering Management

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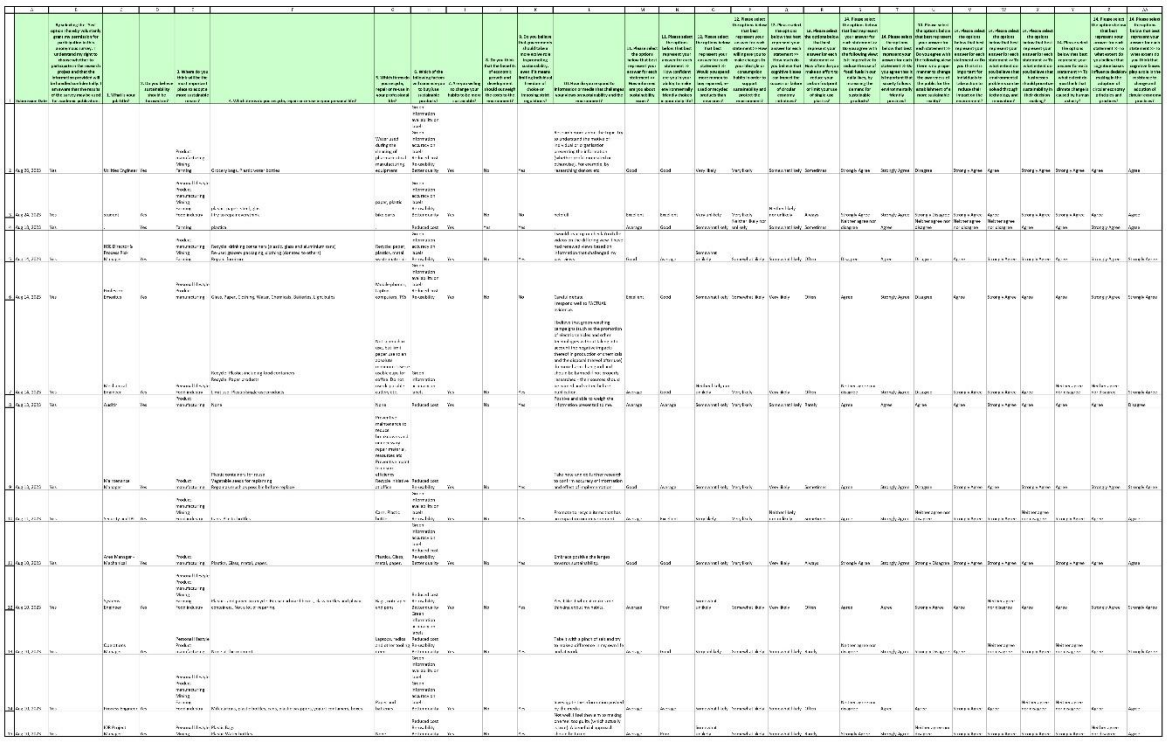
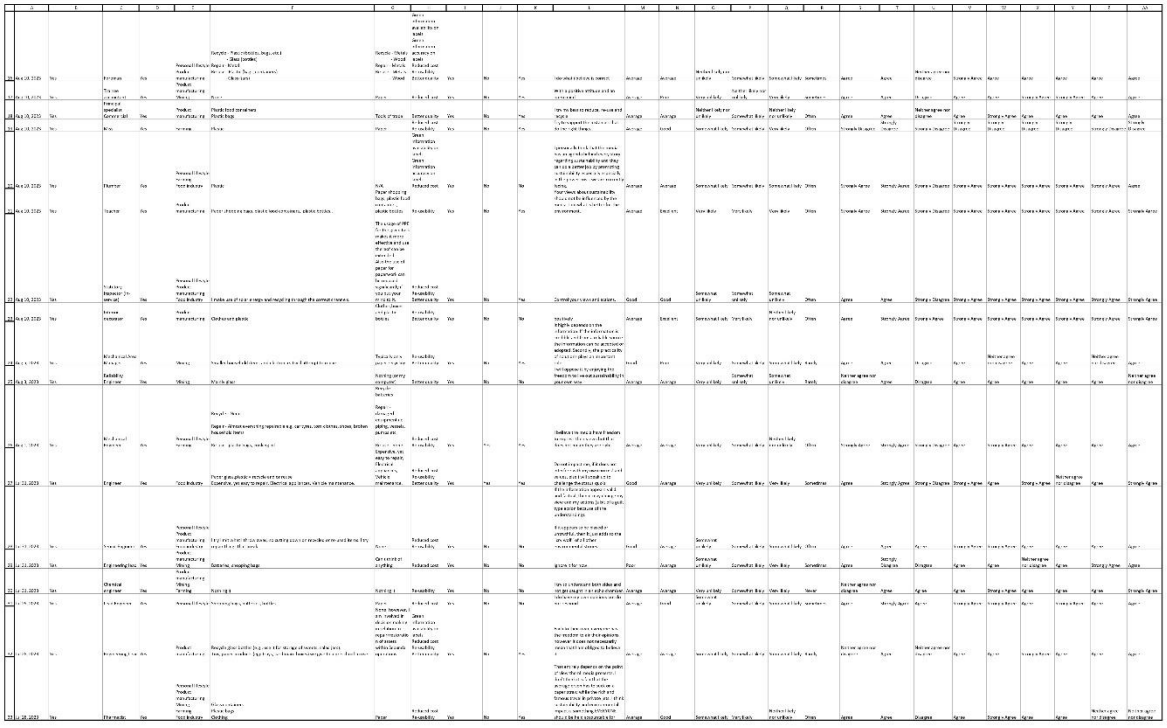
3. Appendix C – Raw data from surveys





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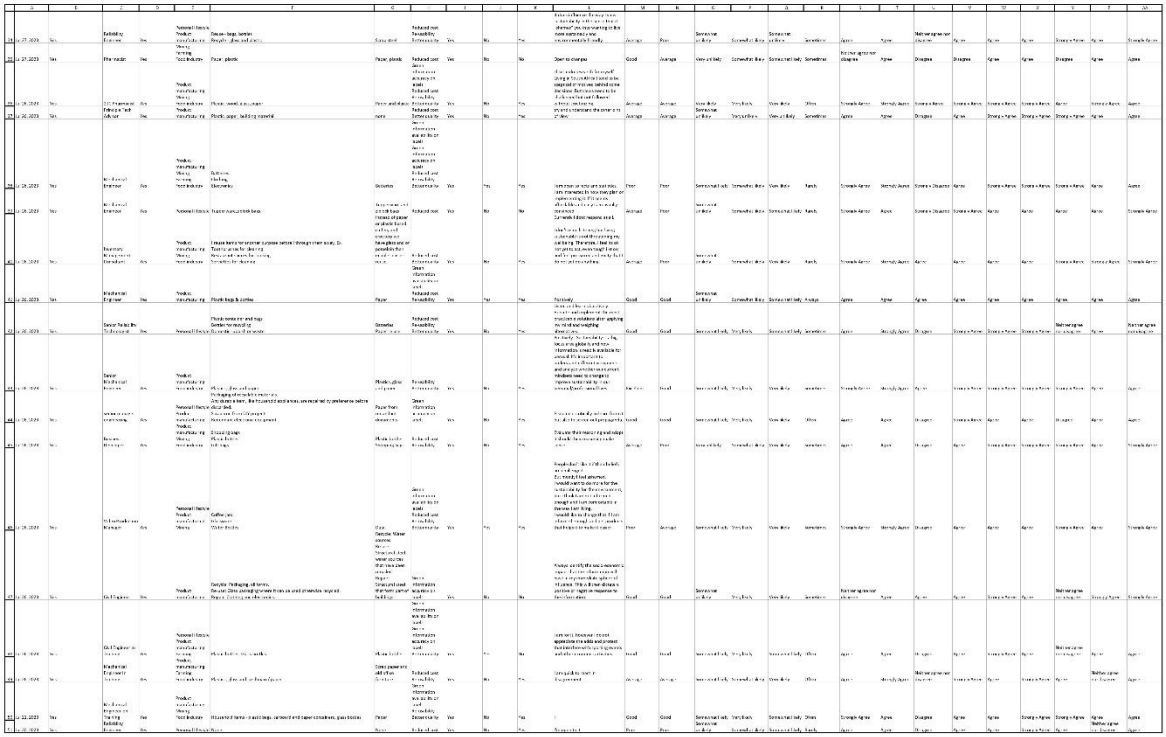

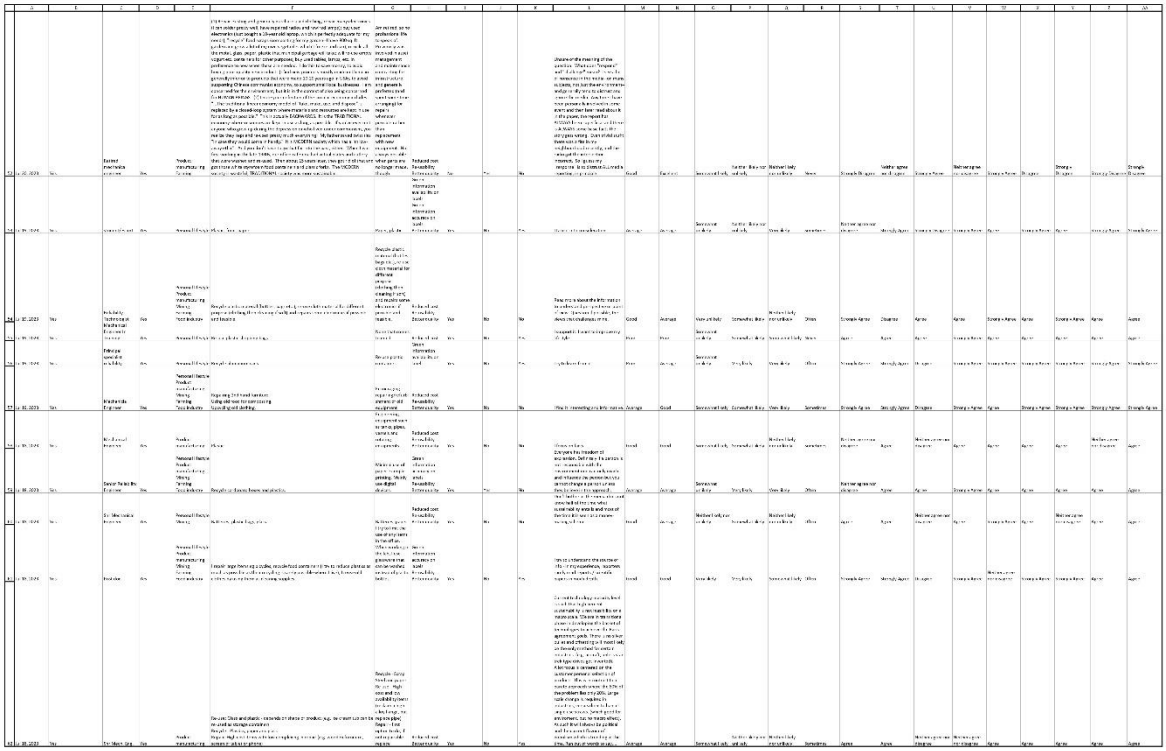

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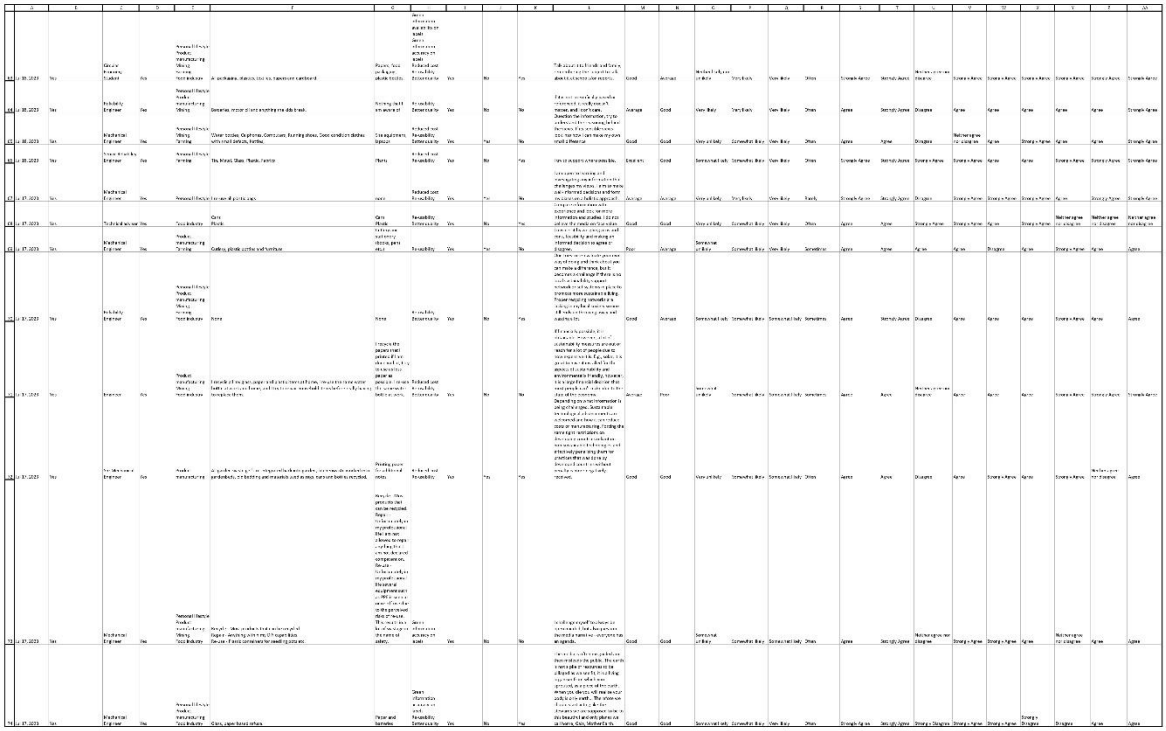

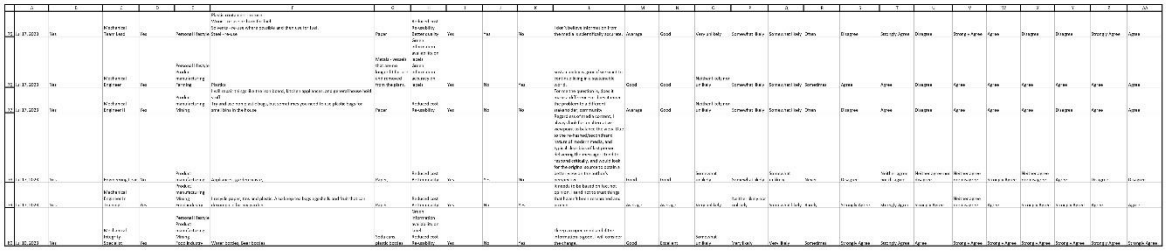

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4. Appendix D – Phyton coding

```
import numpy as np
import pandas as pd
from scipy.stats import weibull_min

# Manually input your response data here.
# Each row corresponds to a respondent, and each column corresponds to a question.
# Example data (replace with your actual data):
data = [
    [1,1,0,1,3,3,4,4,3,2,4,4,1,4,3,4,4,3,3],
[1,1,0,0,4,4,0,4,2,4,4,4,0,4,3,4,4,3,3],
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[1,1,0,1,2,2,0,2,3,1,4,4,4,2,3,4,4,3,3],
[1,1,0,1,3,4,1,4,4,2,4,4,3,4,4,4,4,4,4]
       # Add more rows as needed
]

# Convert to a DataFrame
```


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```
responses = pd.DataFrame(data, columns=[f"Q{i+1}" for i in range(len(data[0]))])

# Function to fit Weibull distribution and return beta and eta parameters
def fit_weibull(data):
    # Fit a Weibull distribution to the data
    params = weibull_min.fit(data, floc=0)
    eta = params[0]  # Shape parameter
    beta = params[2]  # Scale parameter
    return eta, beta

# Create a dictionary to store the beta and eta values for each question
weibull_params = {}

# Loop through each question and fit a Weibull distribution to the answers
for column in responses.columns:
    eta, beta = fit_weibull(responses[column])
    weibull_params[column] = {'eta': eta, 'beta': beta}

# Print the results
for question, params in weibull_params.items():
    #print(f"{question}: eta (shape) = {params['eta']}, beta (scale) = {params['beta']}")
    print(params['eta'],",",params['beta'])
```

```
1.0 , 1.0000000000000226
1.0 , 1.0000000000000226
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3919459174.4219847 , 0.9999999998966689
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3.214266633799516 , 2.6746797788128553
2.2181649424839476 , 2.3936160652873184
1.0 , 1.05
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1.0 , 1.05
1.0 , 1.05
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1.0 , 1.05
1.0 , 1.05
```


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```
import numpy as np
import matplotlib.pyplot as plt

# Define the questions and their possible answers
questions = [
    "Do you believe sustainability should be focused on?",
    "Are you willing to change your habits to be more sustainable?",
    "Do you think that the benefits of economic growth and development should outweigh the costs to the environment?",
    "Do you believe that governments should take a more active role in promoting sustainability, even if it means limiting indivi
    "How informed are you about sustainability issues?",
    "How confident are you in your ability to make environmentally friendly choices in your daily life?",
    "Would you spend more money to buy repaired, re-used or recycled products than new ones?",
    "How willing are you to make changes to your lifestyle or consumption habits in order to support sustainability and protect t
    "How much do you believe that cognitive biases can impact the success or failure of circular economy initiatives?",
    "How often do you make an effort to reduce your carbon footprint or limit your use of single-use plastics?",
    "Do you agree with the following view: Is it imperative to reduce the use of fossil fuels in our daily lives, by increasing t
    "Do you agree that it is important that society follows environmentally friendly practices?",
    "Do you agree with the following view: There is no proper manner to change the awareness of the public for the establishment
    "Do you think it is important for individuals to take action to reduce their impact on the environment?",
    "To what extent do you believe that environmental problems can be solved through technology and innovation?",
    "To what extent do you believe that businesses should prioritize sustainability in their decision-making?",
    "To what extent do you think that climate change is caused by human activity?",
    "To what extent do you believe that cognitive biases influence decision-making in the adoption of circular economy principles
    "To what extent do you think that cognitive biases play a role in the resistance to change and adoption of circular economy p
]

possible_answers = [
    [0, 1],        # Possible answers for Question 1
    [0, 1],        # Possible answers for Question 2
    [0, 1],        # Possible answers for Question 3
    [0, 1],        # Possible answers for Question 4
    [0, 1, 2, 3, 4],  # Possible answers for Question 5
    [0, 1, 2, 3, 4],  # Possible answers for Question 6
    [0, 1, 2, 3, 4],  # Possible answers for Question 7
    [0, 1, 2, 3, 4],  # Possible answers for Question 8
    [0, 1, 2, 3, 4],  # Possible answers for Question 9
    [0, 1, 2, 3, 4],  # Possible answers for Question 10
    [0, 1, 2, 3, 4],  # Possible answers for Question 11
    [0, 1, 2, 3, 4],  # Possible answers for Question 12
    [0, 1, 2, 3, 4],  # Possible answers for Question 13
    [0, 1, 2, 3, 4],  # Possible answers for Question 14
    [0, 1, 2, 3, 4],  # Possible answers for Question 15
    [0, 1, 2, 3, 4],  # Possible answers for Question 16
    [0, 1, 2, 3, 4],  # Possible answers for Question 17
    [0, 1, 2, 3, 4],  # Possible answers for Question 18
    [0, 1, 2, 3, 4]   # Possible answers for Question 19
]

# Weibull distribution parameters for each question (shape, scale)
weibull_params = [
```


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```
    (1.0, 1.0000000000000226),              # Parameters for Question 1
    (1.0, 1.0000000000000226),              # Parameters for Question 2
    (0.049432288581988885, 1.0390235116420852e-24),  # Parameters for Question 3
    (3919459174.4219847, 0.9999999998966689),        # Parameters for Question 4
    (3.6765068815075823, 2.6519105401245233),        # Parameters for Question 5
    (3.214266633799516, 2.6746797788128553),         # Parameters for Question 6
    (2.2181649424839476, 2.3936160652873184),        # Parameters for Question 7
    (1.0, 1.05),              # Parameters for Question 8
    (4.614597686896571, 3.4850376322355663),         # Parameters for Question 9
    (3.4100060358177604, 2.632888251403293),         # Parameters for Question 10
    (4.479142728660216, 3.3446023325942673),         # Parameters for Question 11
    (1.0, 1.05),              # Parameters for Question 12
    (1.9730213836370187, 2.1179699389237245),        # Parameters for Question 13
    (1.0, 1.05),              # Parameters for Question 14
    (1.0, 1.05),              # Parameters for Question 15
    (1.0, 1.05),              # Parameters for Question 16
    (4.428815336421598, 3.448420215752952),          # Parameters for Question 17
    (1.0, 1.05),              # Parameters for Question 18
    (1.0, 1.05)               # Parameters for Question 19
]

# Number of simulations
num_simulations = 1000

# Number of questions
num_questions = len(questions)

# Simulate responses for each question using Weibull distribution
results = []
for i in range(num_questions):
    shape, scale = weibull_params[i]
    simulated_responses = np.random.weibull(shape, size=num_simulations) * scale
    results.append(simulated_responses)

# Plot histograms for each question
plt.figure(figsize=(12, num_questions * 4))  # Adjust figure height based on number of questions

for i in range(num_questions):
    plt.subplot(num_questions, 1, i + 1)
    # Extend the range slightly beyond the maximum possible answer
    max_answer = max(possible_answers[i])
    counts, bins, patches = plt.hist(results[i], bins=max_answer+1, range=(-0.5, max_answer+0.5), align='mid', color='skyblue', e
    plt.xticks(range(max_answer + 1), [str(answer) for answer in range(max_answer + 1)])
    plt.title(questions[i])
    plt.xlabel('Answer')
    plt.ylabel('Frequency')

    # Add bin counts on top of the bars
    for count, patch in zip(counts, patches):
        height = patch.get_height()
        plt.text(patch.get_x() + patch.get_width() / 2., height, int(count), ha='center', va='bottom')

plt.tight_layout()
plt.show()
```


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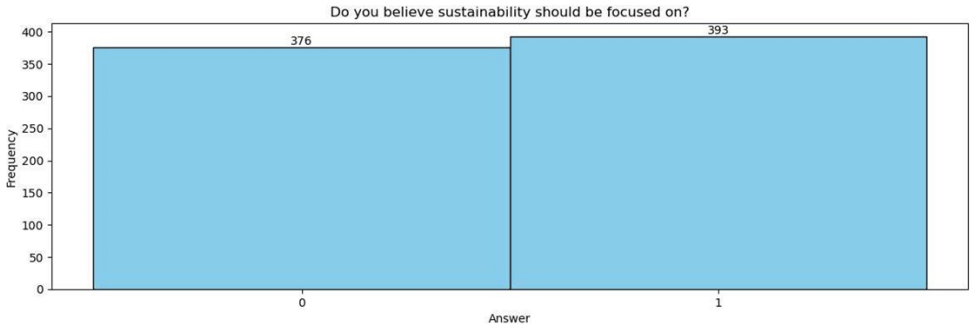
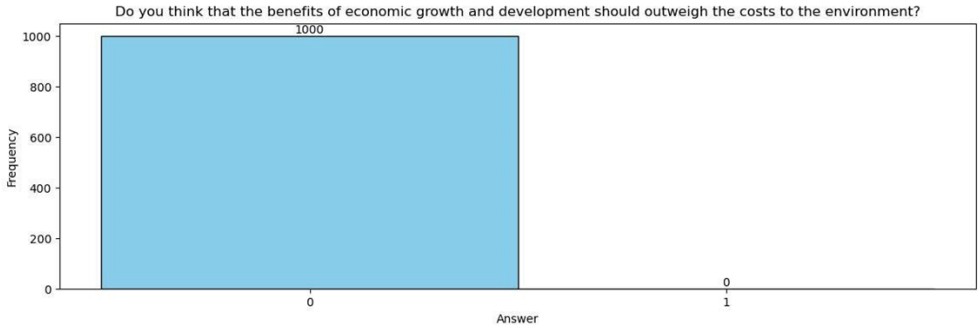
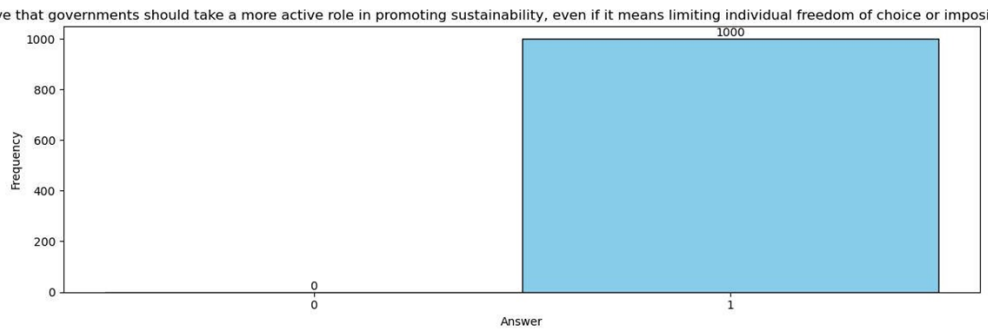
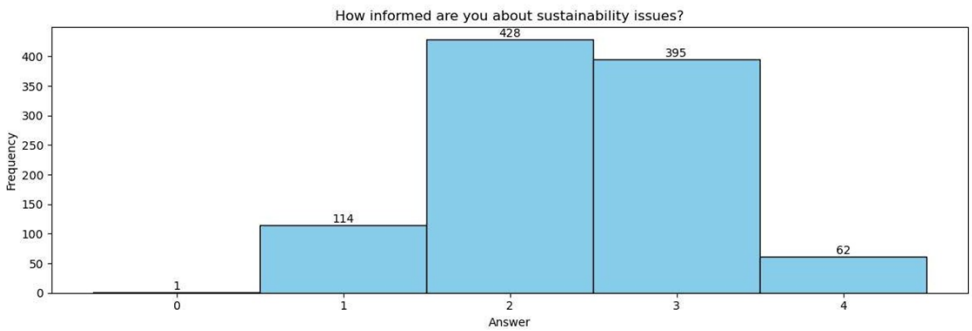
Appendices

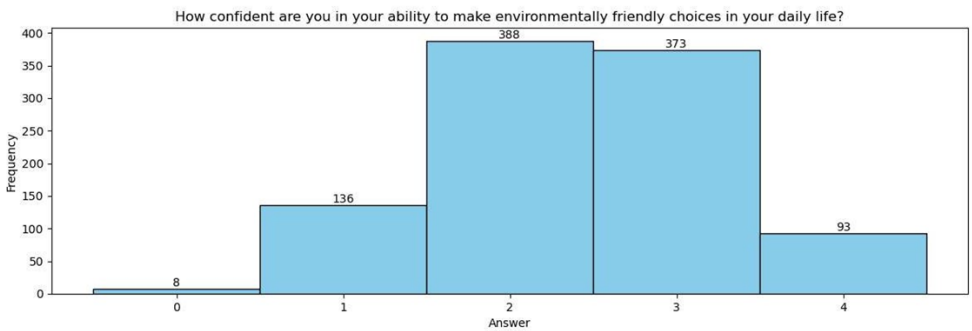




Do you believe that governments should take a more active role in promoting sustainability, even if it means limiting individual freedom of choice or imposing strict regulations?







Would you spend more money on [illegible] products than new ones?

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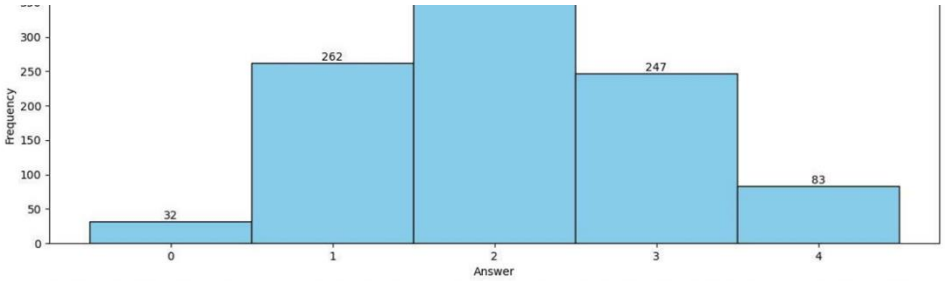
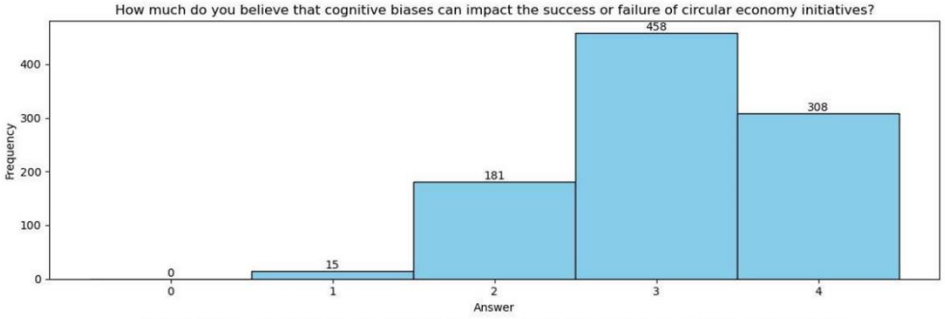
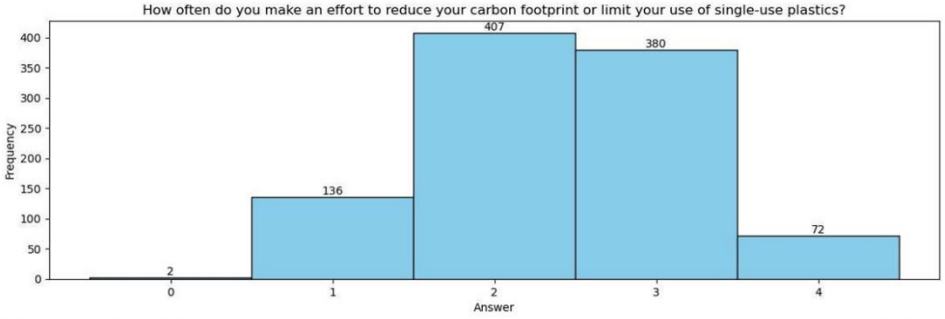


How willing are you to make changes to your lifestyle or consumption habits in order to support sustainability and protect the environment?

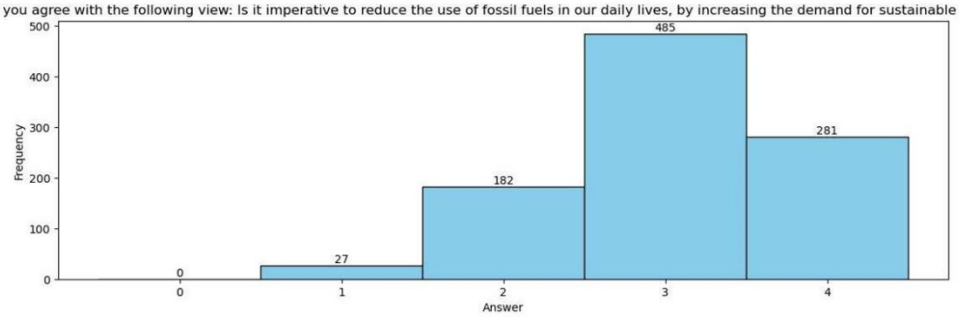
How much do you believe that cognitive biases can impact the success or failure of circular economy initiatives?



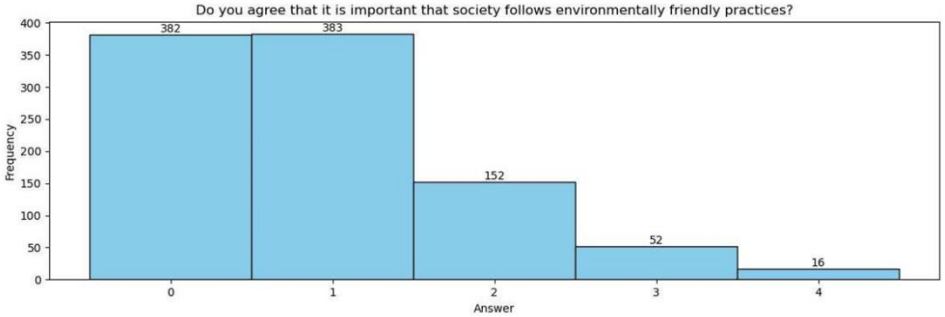
How often do you make an effort to reduce your carbon footprint or limit your use of single-use plastics?



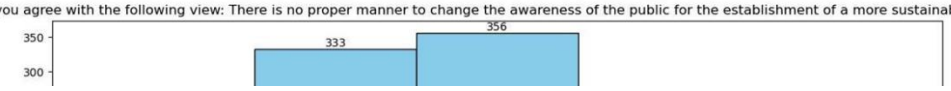
Do you agree with the following view: Is it imperative to reduce the use of fossil fuels in our daily lives, by increasing the demand for sustainable products?



Do you agree that it is important that society follows environmentally friendly practices?



Do you agree with the following view: There is no proper manner to change the awareness of the public for the establishment of a more sustainable reality?



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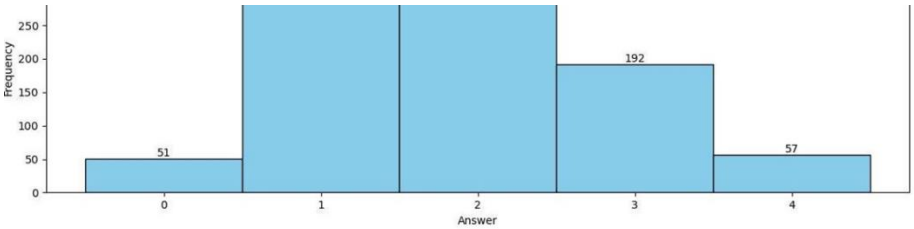
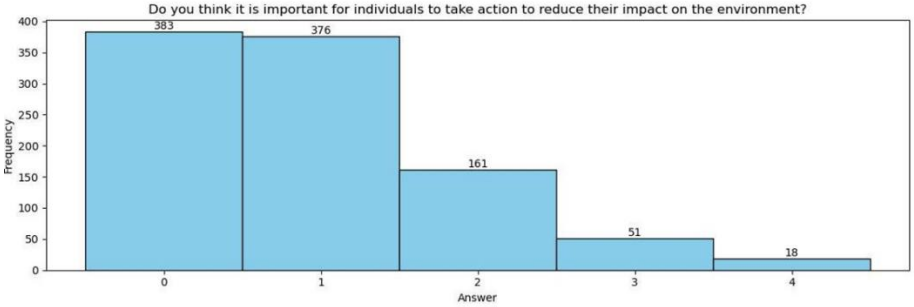
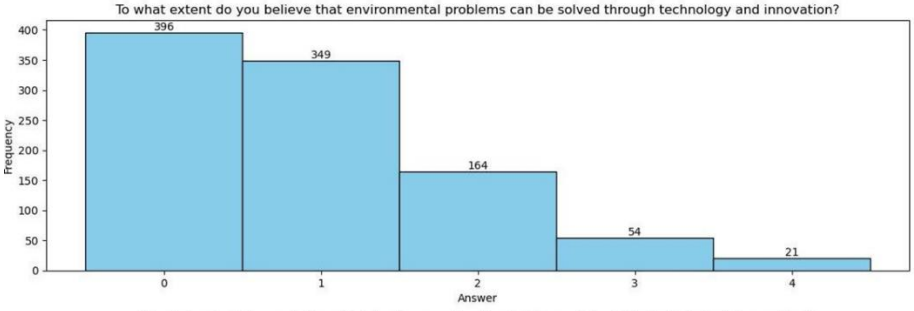


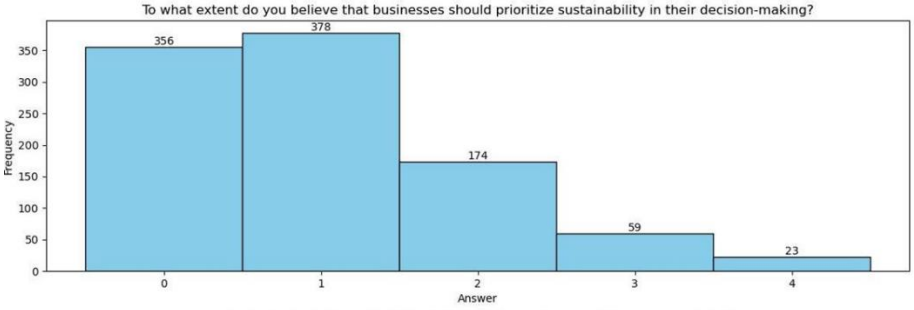
Do you think it is important for individuals to take action to reduce their impact on the environment?



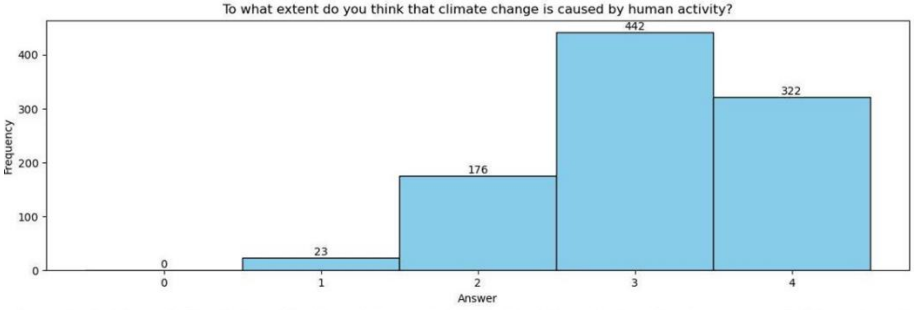
To what extent do you believe that environmental problems can be solved through technology and innovation?



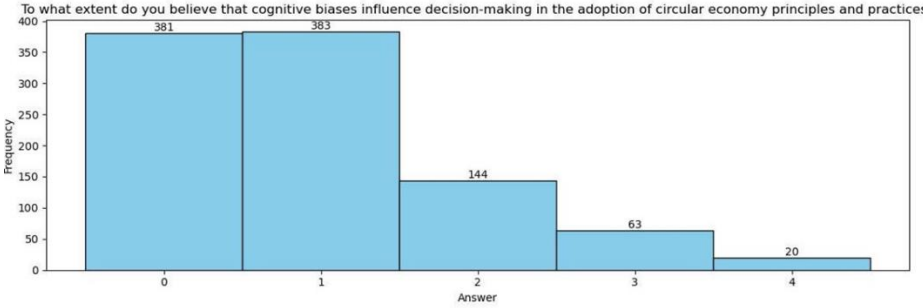
To what extent do you believe that businesses should prioritize sustainability in their decision-making?



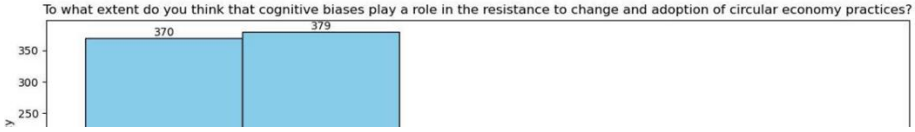
To what extent do you think that climate change is caused by human activity?



To what extent do you believe that cognitive biases influence decision-making in the adoption of circular economy principles and practices?



To what extent do you think that cognitive biases play a role in the resistance to change and adoption of circular economy practices?



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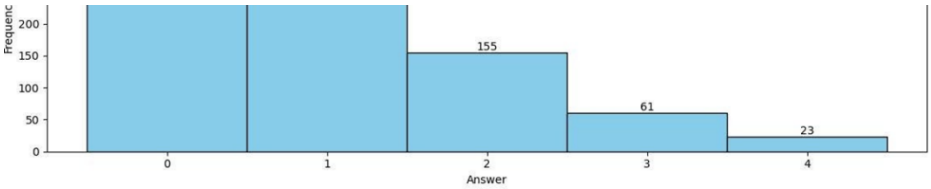


```
import matplotlib.pyplot as plt
import pandas as pd

# Data: each row represents a person's response to 19 questions
data = [
    [1,1,0,1,3,3,4,4,3,2,4,4,1,4,3,4,4,3,3],
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```


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```
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    [1,1,0,1,3,4,1,4,4,2,4,4,3,4,4,4,4,4,4]
]

# Convert the list of lists into a DataFrame
df = pd.DataFrame(data)

# Plot histograms for each question
num_questions = df.shape[1]

plt.figure(figsize=(15, 15))

for i in range(num_questions):
    plt.subplot(5, 4, i + 1)  # Create a grid of 5x4 subplots
    plt.hist(df[i], bins=range(0, 6), edgecolor='black', alpha=0.7)
    plt.title(f'Question {i + 1}')
    plt.xlabel('Response')
    plt.ylabel('Frequency')
    plt.xticks(range(0, 5))

plt.tight_layout()
plt.show()
```


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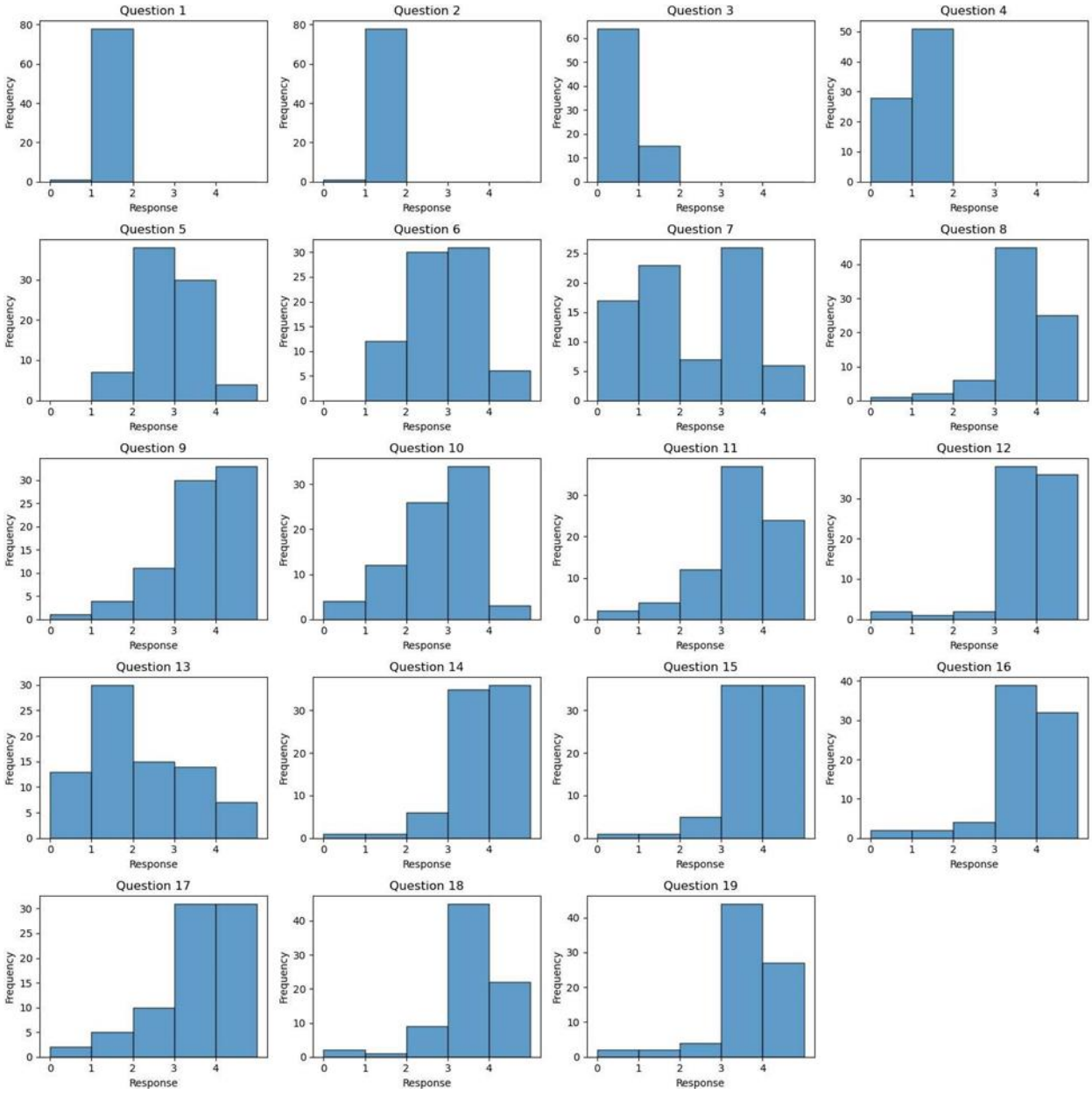

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```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from scipy import stats

# Convert data to DataFrame
df = pd.DataFrame(data)

# Determine the number of questions
num_questions = df.shape[1]

# Create a figure with subplots
fig, axs = plt.subplots(nrows=(num_questions + 2) // 3, ncols=3, figsize=(15, 5 * ((nu
fig.tight_layout(pad=5.0)

# Flatten the axes array for easy iteration
axs = axs.flatten()

# Fit and plot normal distribution for each question
for i in range(num_questions):
    responses = df.iloc[:, i]
```

```
    # Fit a normal distribution
    mu, std = stats.norm.fit(responses)

    # Create a histogram
    axs[i].hist(responses, bins=10, density=True, alpha=0.6, color='g')

    # Plot the normal distribution
    xmin, xmax = axs[i].get_xlim()
    x = np.linspace(xmin, xmax, 100)
    p = stats.norm.pdf(x, mu, std)
    axs[i].plot(x, p, 'k', linewidth=2)

    axs[i].set_title(f'Question {i + 1} - Normal Distribution Fit')
    axs[i].set_xlabel('Response')
    axs[i].set_ylabel('Density')

# Hide any unused subplots
for j in range(num_questions, len(axs)):
    axs[j].axis('off')

plt.show()
```


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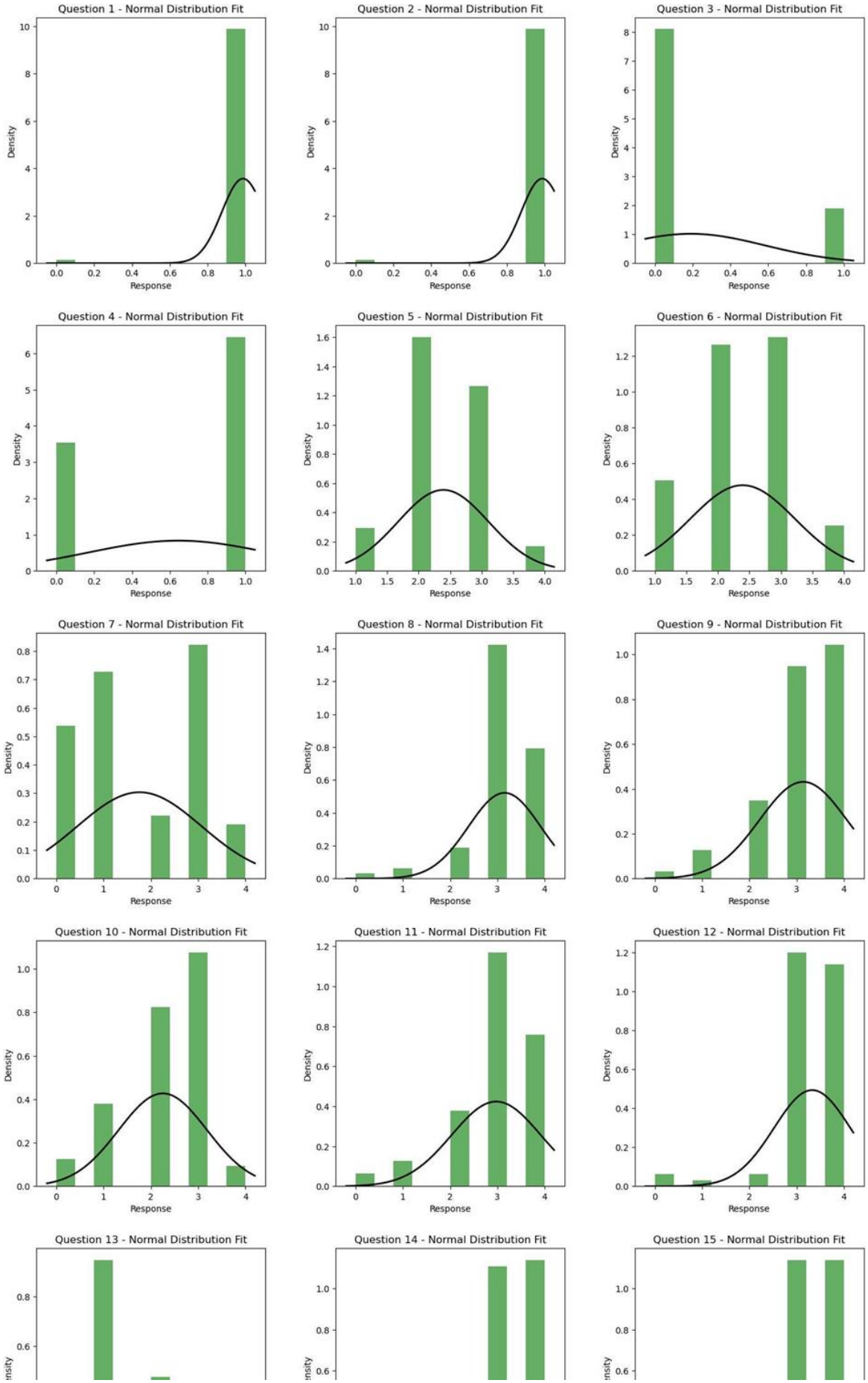

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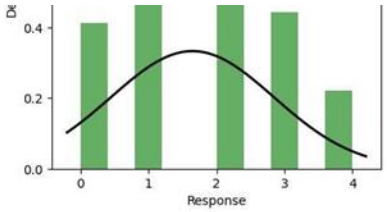

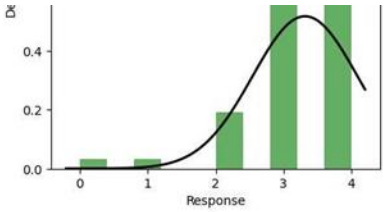

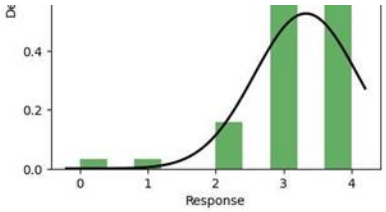

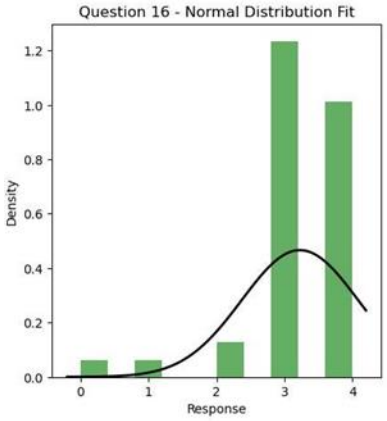

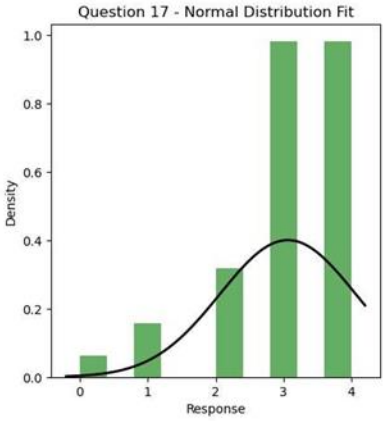

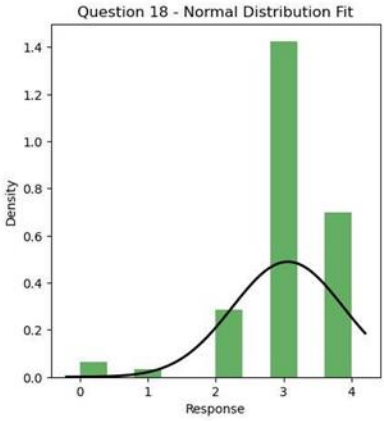

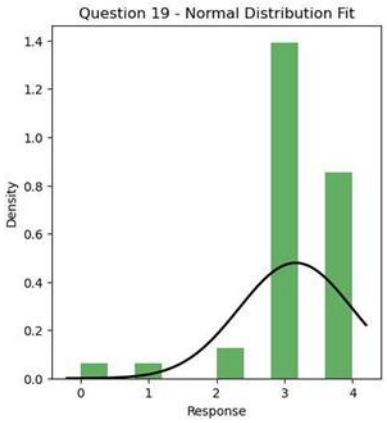


```python
import numpy as np
from scipy import stats

# Convert data to DataFrame
df = pd.DataFrame(data)

# Fit normal distribution and print parameters for each question
params = []
for i in range(df.shape[1]):
    responses = df.iloc[:, i]

    # Fit a normal distribution
    mu, std = stats.norm.fit(responses)

    # Store parameters
    params.append((mu, std))
    print(f'Question {i + 1} - Mean: {mu:.2f}, Std Dev: {std:.2f}')

# Optionally, convert params to DataFrame for better visualization
params_df = pd.DataFrame(params, columns=['Mean', 'Std Dev'])
print("\nNormal Distribution Parameters for each question:")
print(params_df)
```


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```
Question 1 - Mean: 0.99, Std Dev: 0.11
Question 2 - Mean: 0.99, Std Dev: 0.11
Question 3 - Mean: 0.19, Std Dev: 0.39
Question 4 - Mean: 0.65, Std Dev: 0.48
Question 5 - Mean: 2.39, Std Dev: 0.72
Question 6 - Mean: 2.39, Std Dev: 0.83
Question 7 - Mean: 1.76, Std Dev: 1.31
Question 8 - Mean: 3.15, Std Dev: 0.76
Question 9 - Mean: 3.14, Std Dev: 0.92
Question 10 - Mean: 2.25, Std Dev: 0.93
Question 11 - Mean: 2.97, Std Dev: 0.94
Question 12 - Mean: 3.33, Std Dev: 0.81
Question 13 - Mean: 1.65, Std Dev: 1.20
Question 14 - Mean: 3.32, Std Dev: 0.77
Question 15 - Mean: 3.33, Std Dev: 0.76
Question 16 - Mean: 3.23, Std Dev: 0.86
Question 17 - Mean: 3.06, Std Dev: 1.00
Question 18 - Mean: 3.06, Std Dev: 0.82
Question 19 - Mean: 3.16, Std Dev: 0.83

Normal Distribution Parameters for each question:
        Mean   Std Dev
0   0.987342  0.111794
1   0.987342  0.111794
2   0.189873  0.392201
3   0.645570  0.478340
4   2.392405  0.718961
5   2.392405  0.833138
6   1.759494  1.314141
7   3.151899  0.764540
8   3.139241  0.924137
9   2.253165  0.934139
10  2.974684  0.940976
11  3.329114  0.806956
12  1.645570  1.201665
13  3.316456  0.772048
14  3.329114  0.758438
15  3.227848  0.856093
16  3.063291  0.997995
17  3.063291  0.816627
18  3.164557  0.833331
```

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats

# Parameters for each question
params_df = pd.DataFrame({
    'Mean': [0.99, 0.99, 0.19, 0.65, 2.39, 2.39, 1.76, 3.15, 3.14, 2.25, 2.97, 3.33, 1
    'Std Dev': [0.11, 0.11, 0.39, 0.48, 0.72, 0.83, 1.31, 0.76, 0.92, 0.93, 0.94, 0.81
})

# Number of simulations
num_simulations = 5000

# Plot settings
plt.figure(figsize=(15, 10))

for i in range(params_df.shape[0]):
```


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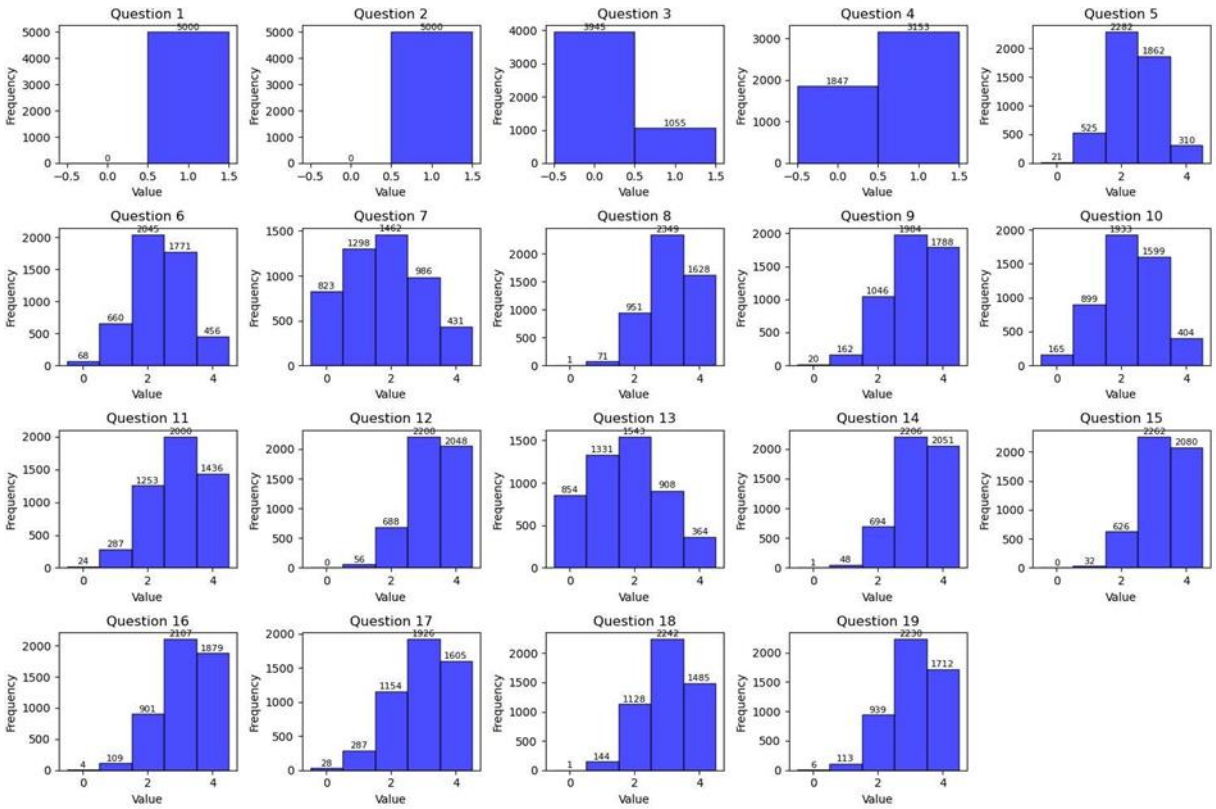
```
    mu = params_df.loc[i, 'Mean']
    sigma = params_df.loc[i, 'Std Dev']

    # Generate 5000 samples based on the normal distribution
    simulated_data = np.random.normal(loc=mu, scale=sigma, size=num_simulations)

    # Apply rounding and restriction
    if i < 4:  # Questions 1 to 4
        simulated_data = np.round(simulated_data).astype(int)
        simulated_data = np.clip(simulated_data, 0, 1)
    else:  # Questions 5 to 19
        simulated_data = np.round(simulated_data).astype(int)
        simulated_data = np.clip(simulated_data, 0, 4)

    # Plot the histogram of the simulated data
    plt.subplot(4, 5, i + 1)

    if i < 4:
        bins = np.arange(-0.5, 1.6, 1)
    else:
        bins = np.arange(-0.5, 4.6, 1)

    counts, _ = np.histogram(simulated_data, bins=bins)
    plt.hist(simulated_data, bins=bins, alpha=0.7, color='blue', edgecolor='black')

    # Add counts to the plot
    for j, count in enumerate(counts):
        plt.text(bins[j] + 0.5, count + 10, str(count), ha='center', va='bottom', font

    plt.title(f'Question {i + 1}')
    plt.xlabel('Value')
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```



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5. Appendix E – Interview Information – Model Development 1

	● #External social elements Gr=65	● #Internal social elements Gr=37	● CE: Butterfly diagram Gr=12	● CE: GDP based Gr=25	● CE: Human links Gr=56	● CE: Industry based Gr=37	● Circular Economy (CE) Gr=81	● HD: Abilities Gr=41	● HD: Welfare Gr=33	● Human Development (HD) Gr=8	● SE: Human Systems Integration Gr=15	● Social elements Gr=24	● ST: Bigger picture Gr=24	● ST: Understand the system Gr=57	● Sustainable Development Goals (SDG) Gr=12	● Systems Engineering (SE) Gr=7	● Systems Thinking (ST) Gr=42
● #External social elements Gr=65	0	4	3	10	27	11	21	20	12	1	4	2	10	15	3	3	7
● #Internal social elements Gr=37	4	0	2	3	11	7	15	8	4	0	3	3	3	7	0	1	7
● CE: Butterfly diagram Gr=12	3	2	0	0	4	0	4	3	1	0	0	1	1	2	0	0	0
● CE: GDP based Gr=25	10	3	0	0	6	3	10	7	4	0	0	1	0	3	2	0	1
● CE: Human links Gr=56	27	11	4	6	0	13	13	15	8	1	7	5	8	19	1	2	6
● CE: Industry based Gr=37	11	7	0	3	13	0	17	12	8	1	0	4	4	14	1	1	7
● Circular Economy (CE) Gr=81	21	15	4	10	13	17	0	16	7	6	9	7	5	19	5	4	19
● HD: Abilities Gr=41	20	8	3	7	15	12	16	0	11	4	1	2	5	13	0	0	6
● HD: Welfare Gr=33	12	4	1	4	8	8	7	11	0	2	1	4	4	6	3	0	4
● Human Development (HD) Gr=8	1	0	0	0	1	1	6	4	2	0	0	0	0	0	1	0	0
● SE: Human Systems Integration Gr=15	4	3	0	0	7	0	9	1	1	0	0	3	2	4	0	1	1
● Social elements Gr=24	2	3	1	1	5	4	7	2	4	0	3	0	2	6	1	1	3
● ST: Bigger picture Gr=24	10	3	1	0	8	4	5	5	4	0	2	2	0	11	1	0	11
● ST: Understand the system Gr=57	15	7	2	3	19	14	19	13	6	0	4	6	11	0	0	0	22
● Sustainable Development Goals (SDG) Gr=12	3	0	0	2	1	1	5	0	3	1	0	1	1	0	0	0	0
● Systems Engineering (SE) Gr=7	3	1	0	0	2	1	4	0	0	0	1	1	0	0	0	0	2
● Systems Thinking (ST) Gr=42	7	7	0	1	6	7	19	6	4	0	1	3	11	22	0	2	0

Figure 126. Code co-occurrence of interview transcript themes – Model Development 1

Location	Designation	Contact population	Rejections	Actual responses	Interviewed	Proposed sample	Interiew success rate	Interview reponse rate
National	Systems specialists	7	1	4	2	3	29%	50%
	CE specialists	9	1	3	3	3	33%	100%
International	Systems specialists	4	0	0	0	3	0%	0%
	CE specialists	34	1	4	3	3	9%	75%
Total		**54**	**3**	**11**	**8**	**12**	**15%**	**73%**

Location	Designation	Interiew success rate	Interview reponse
National	Systems specialists	29%	50%
	CE specialists	33%	100%
International	Systems specialists	0%	0%
	CE specialists	9%	75%
Total		15%	73%

Figure 127. Response data for interviews - Model Development 1

Questionaire:

Question 1:

By selecting the "Yes" option I hereby voluntarily grant my permission for participation in this interview. The nature and the objective of this research have been explained to me and I understand it.

I understand my right to choose whether to participate in the research project and that the information provided will be handled confidentially. I am aware that the results of the interview may be used for academic publication.

□ Yes

□ No

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Question 2:
Discussion on the background of the need of the study
In the INCOSE Newsletter 2020 for Quarter 3, Kerry Lunney (President of INCOSE) describes a few examples where systems engineering are applied. In each of the examples it is clear that the sociotechnical aspect, sustainability, and resilience are becoming increasingly fundamental in assessing the success of any system. The evolution of the breadth in systems engineering is evident. The balance between the quality in people's work lives and technical performance excellence is important in engineering systems.

CE focuses on continual material value-add in order to manage waste, but this has not proven to be the end-to-end solution to the waste and pollution problem faced by the world currently. The speed of material flow in the so-called material loop needs to be decreased. This can only be done by reducing demand and endorsing renewable use. The answer to the question, why do we need to introduce the HD elements in the current CE framework, is simply – to successfully slow the material loop.

What is your opinion on the need to focus CE on sustainability through adding the social element?

Question 3:
Discussion on current CE framework
Material life cycles are currently represented by CE, with cost, time and energy inputs. Discussion on the figure below about the current framework to establish where the social elements can be included in each stage.

Is there a stage where human stakeholders can be included to improve sustainability?

Question 4:
Discussion on the proposed CE-HD conceptual model, how can this be further elaborates/changed?

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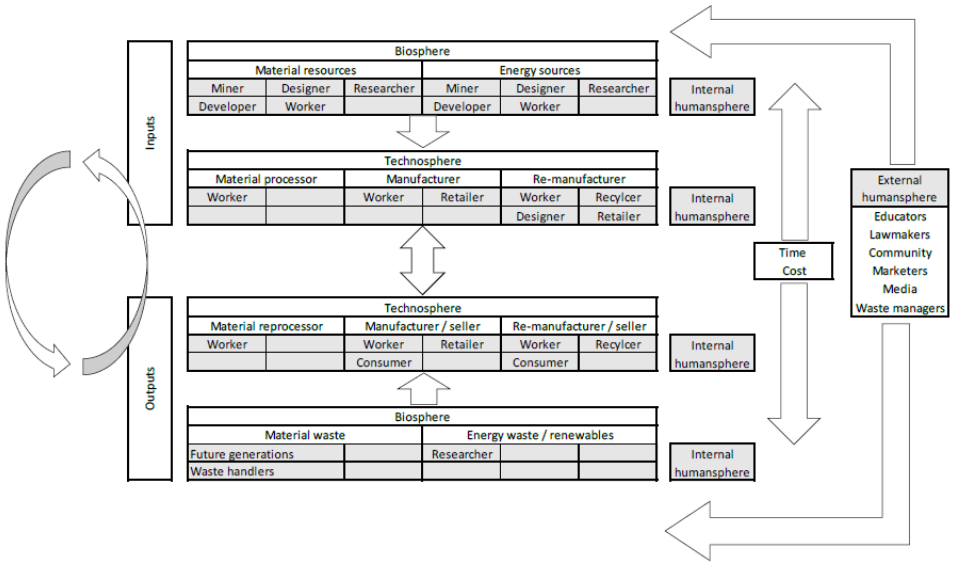
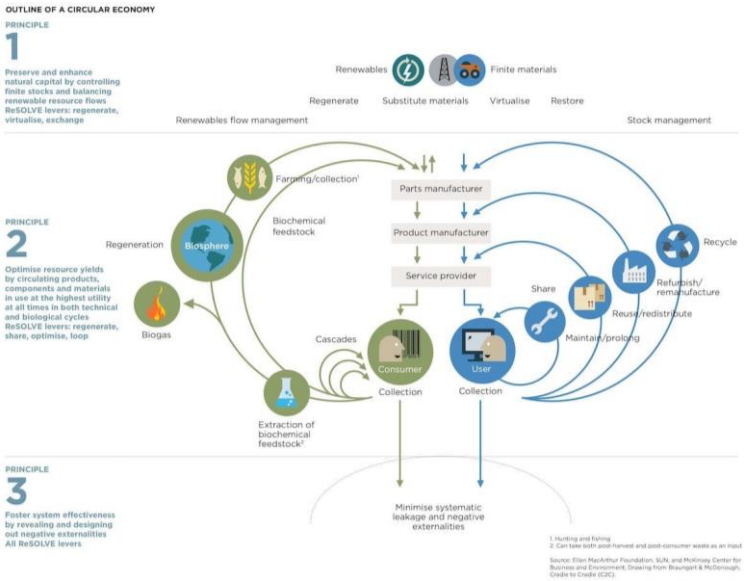
The theoretical framework below aims at presenting that CE offers a way of accomplishing the objective of economic and environmental sustainability, specifically the global challenge to meet sustainable development goals. CE has gained substantial traction in the last few years supporting sustainability. This research aims to show that through academic discourse and practical applications the pitfall in the current CE framework identified - CE frameworks are techno-centric - excludes an integral part of human concerns and that this could be addressed by this research.



Question 5:

The Ellen McArthur Foundation has developed a framework for CE which indicate a few social elements below:

Would the proposed conceptual framework previously, address the other social aspects not mentioned below?



Question 6:

Discussion on Sustainable Development Goals and plastic and steel industry application of proposed conceptual model

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6. Appendix F – Atlas.ti information – Model Development 1

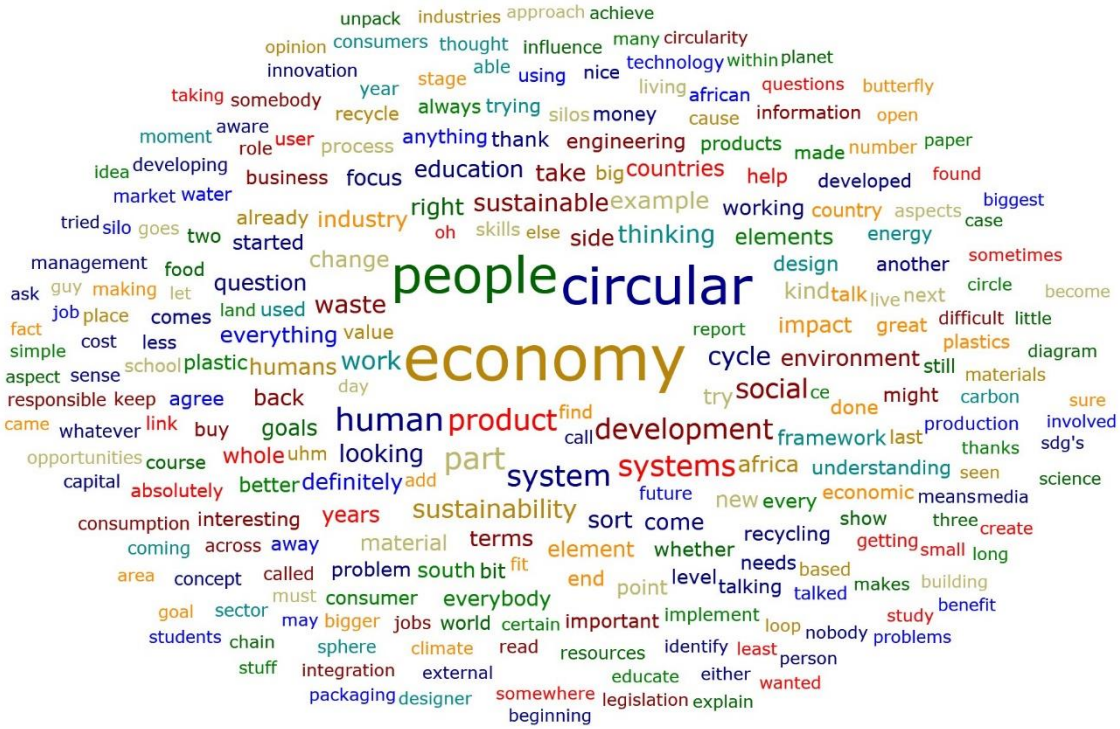

Figure 128. Thematic word cloud from interview transcripts - Model Development 1

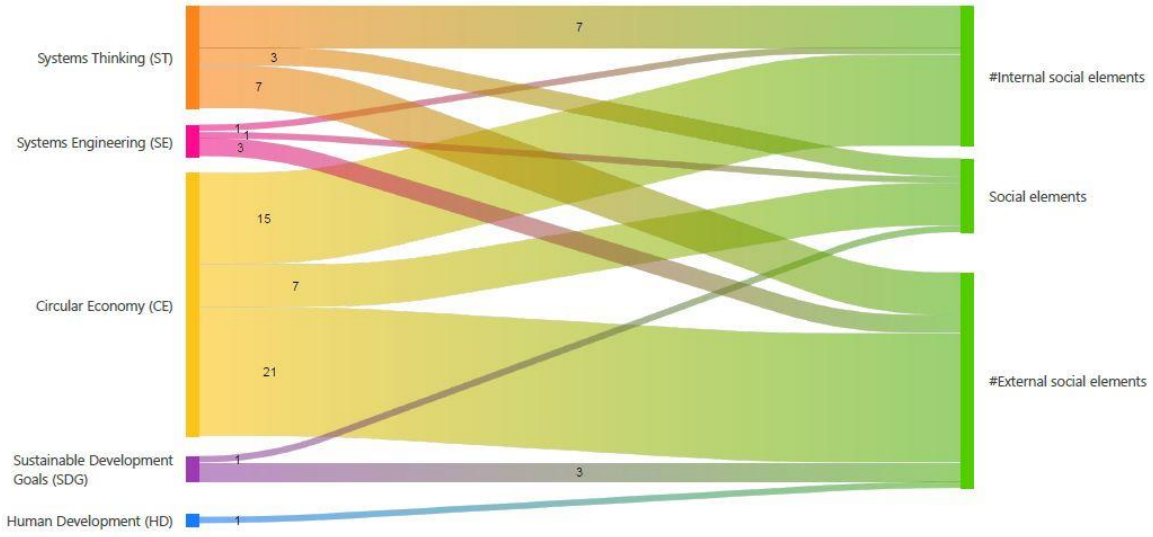

Figure 129. Sankey diagram - Model Development 1

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Document Group	Code
Social/human/people	#External social elements #Internal social elements CE: Human links HD: Abilities HD: Welfare Human Development (HD) SE: Human Systems Integration Social elements
Systems/modelling	SE: Human Systems Integration ST: Bigger picture ST: Understand the system Systems Engineering (SE) Systems Thinking (ST)
Sustainability	CE: Butterfly diagram CE: GDP based CE: Industry based Circular Economy (CE) Sustainable Development Goals (SDG)

Figure 130. Code group manager - Model Development 1

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7. Appendix G – Model Development 4 – Atlas.ti screenshots

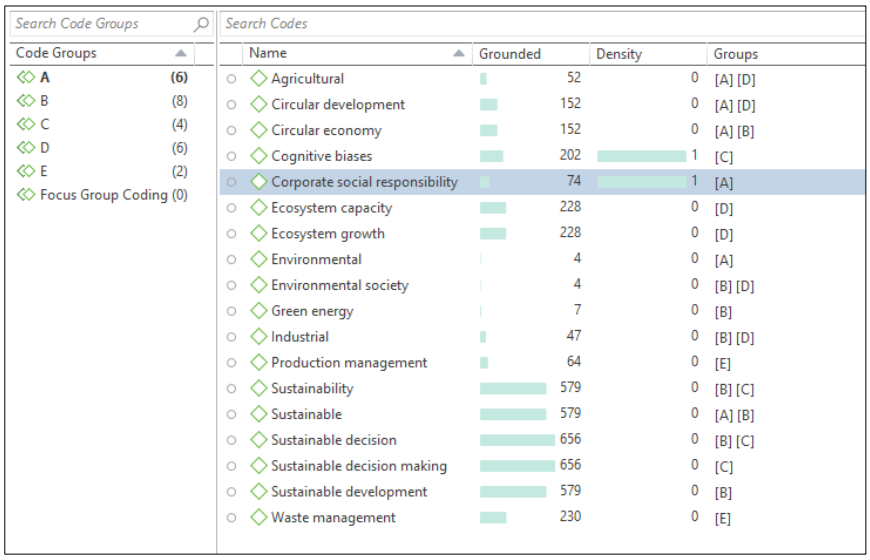

Figure 131. Code manager for Grounded theory - Model Development 4

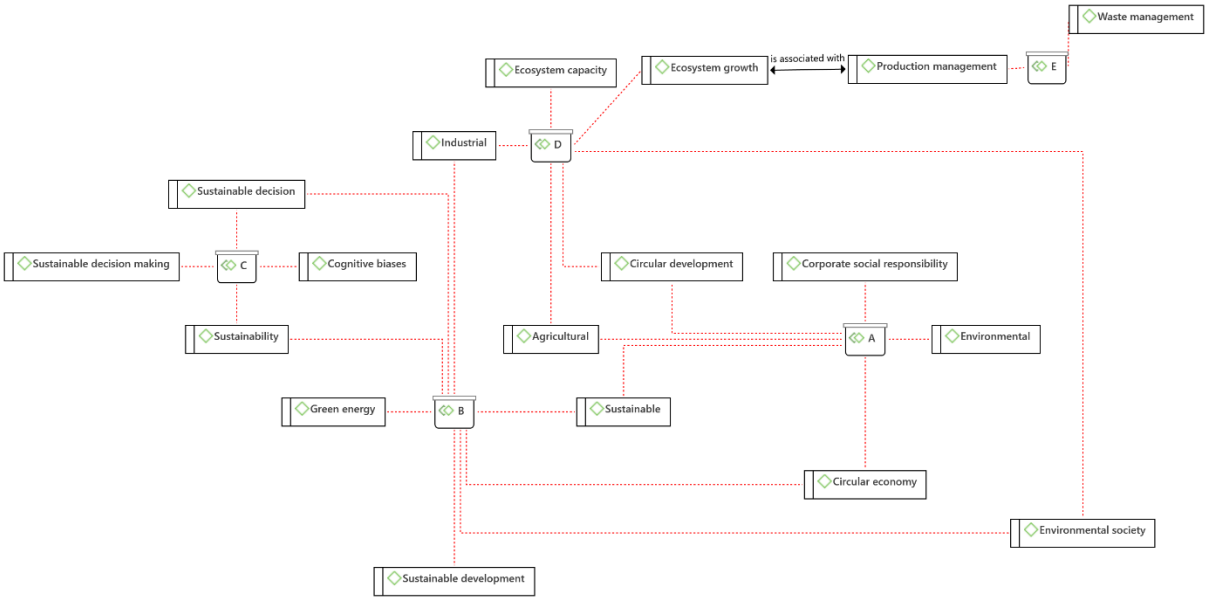

Figure 132. Code network for Grounded theory - Model Development 4

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Code	Occurrence in CLD
○ Corporate social responsibility Gr=82	8
○ Sustainable decision making Gr=663	7
○ Sustainable decision Gr=662	6
○ Cognitive biases Gr=207	5
○ Circular development Gr=156	4
○ Environmental society Gr=8	4
○ Waste management Gr=234	4
○ Agricultural Gr=55	3
○ Ecosystem capacity Gr=231	3
○ Ecosystem growth Gr=231	3
○ Environmental Gr=7	3
○ Green energy Gr=10	3
○ Industrial Gr=50	3
○ Sustainability Gr=582	3
○ Sustainable development Gr=582	3
○ Circular economy Gr=154	2
○ Production management Gr=66	2
○ Sustainable Gr=581	2

Coded groups	Occurrence in CLD
A Gr=870; GS=6	9
B Gr=875; GS=8	9
C Gr=867; GS=4	9
D Gr=490; GS=6	7
E Gr=298; GS=2	4

Figure 133.Code co-occurrence in CLD by code and code group - Model Development 4

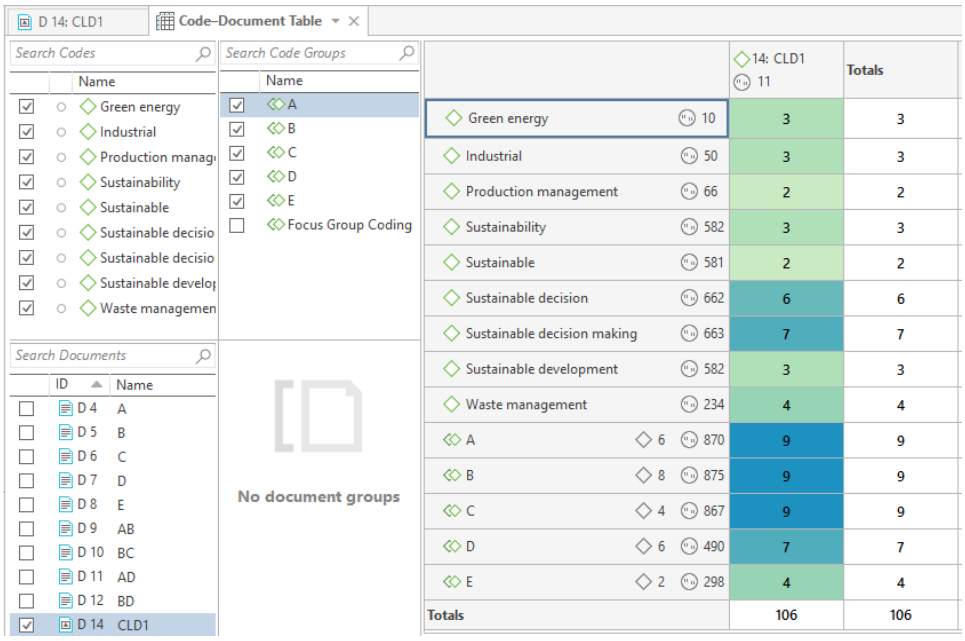

Figure 134. Grounded theory applied to codes and CLD - Model Development 4

	Main topic	Subtopics		Wildcard and search operators	Number of papers
A	Circular Economy	Environmental and corporate responsibility		(environment* responsibility OR "corporate responsibility") AND "circular economy"	25
B	Sustainable society	Sustainable behaviour	Standard of life	(sustainable behavio$r OR "standard of life") AND "sustainab* society"	5
C	Need for sustainable decisions	Supportive cognitive biases	Opposing cognitive biases	("cognitive bias") AND sustainab* AND decisions	30
D	Reaching ecosystem capacity limit	Maintenance	Redistribution	(maintenance OR redistribution) AND ecosystem capacity limit	49
E	Unsustainable consumption and production patterns	Mindset of unlimited economic growth	Waste generation	("unlimited economic growth" OR "waste generation") AND ("unsustainable consumption" OR "production patterns")	12
AB				"Circular Economy" AND" Sustainable society"	53
BC				"Sustainable society" AND "sustainable decisions"	7
AD				"Circular Economy" AND ecosystem capacity limit	4
BD				"Sustainable society" AND ecosystem capacity limit	1
DE				ecosystem capacity limit AND ("Unsustainable consumption" OR "production patterns")	0

Figure 135. Keyword search through databases - Model Development 4

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8. Appendix H – Model Development 5

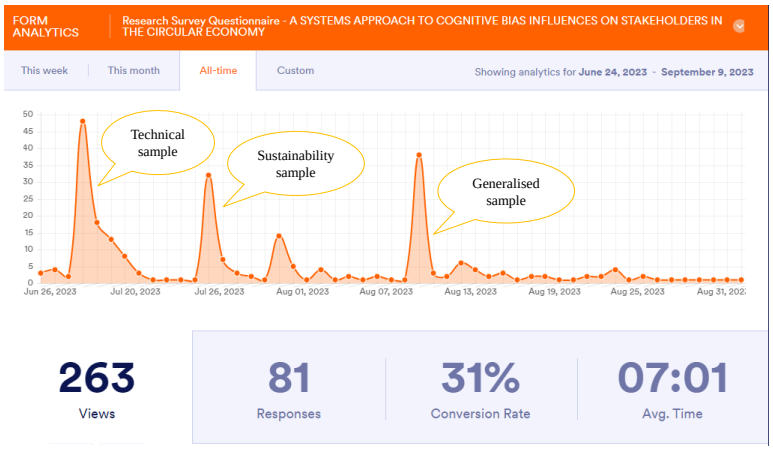

Figure 136. Survey analytics and response rate. Model Development 5

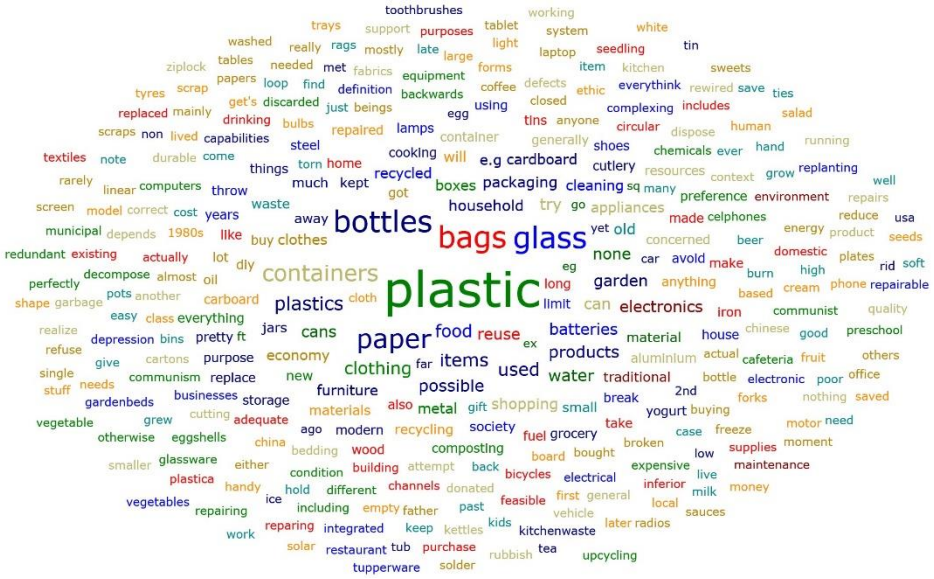

Figure 137. Survey question 2 - wordcloud

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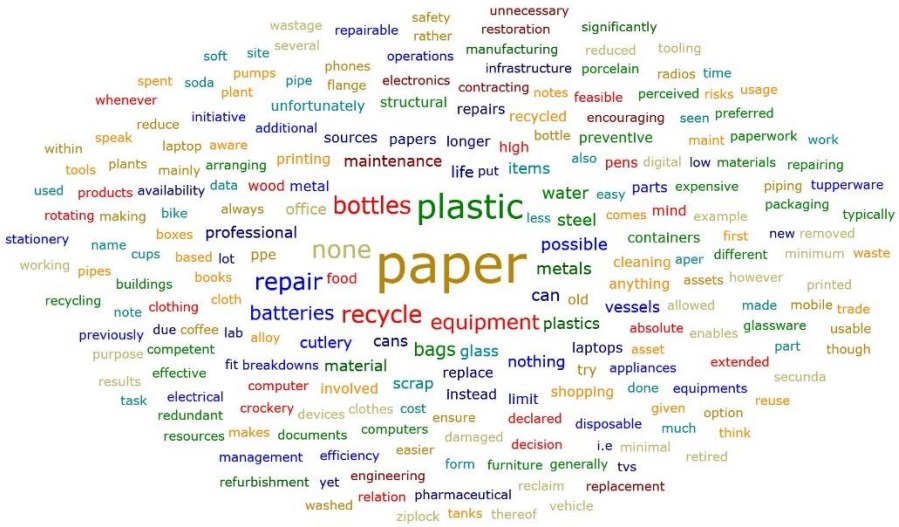

Figure 138. Survey question 3 – wordcloud

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9. Appendix I – Model Development 7

	○ Agreement with fossil fuel reduction Gr=10	○ Agreement with sustainable practices Gr=21	○ Individual action Gr=23	○ Media influence Gr=48	○ Response to information Gr=37	○ Technology & innovation impact Gr=4
○ Negative Gr=26	3	9	7	18	14	2
○ Neutral Gr=16	3	3	6	10	7	2
○ Positive Gr=36	5	10	10	20	17	1

Figure 139. Questions 6 and 10 - Code co-occurrence table with grounded values

	○ Better quality Gr=44	○ Green info accuracy Gr=21	○ Green info available Gr=33	○ Reduced cost Gr=52	○ Reusable Gr=53
○ SQ6 Gr=94	53	29	48	61	63

Figure 140. Thematic analysis of Question 6 with grounded values

Figure 141. Word cloud for all imported survey data to validate them

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Document Group		Count		
biaseresistancetochangeCE::Strongly Agree	Strongly Agree	27	Anchor	14. Please select the options below that best represent your answer for each statement >> To what extent do you think that cognitive biases play a role in the resistance to change and adoption of circular economy practices?
biaseresistancetochangeCE::Agree	Agree	44		
biaseresistancetochangeCE::Neither agree nor disagree	Neither agree nor dis	4		
biaseresistancetochangeCE::Disagree	Disagree	2		
biaseresistancetochangeCE::Strongly Disagree	Strongly Disagree	2		
biasescircular::Very likely	Very likely	33		
biasescircular::Somewhat likely	Somewhat likely	30		
biasescircular::Neither likely nor unlikely	Neither likely nor unl	11		
biasescircular::Somewhat unlikely	Somewhat unlikely	4		
biasescircular::Very unlikely	Very unlikely	1		
biasesinfluencedecision-makingcirculareconomy::Strongly Agree	Strongly Agree	22	Confirmation	14. Please select the options below that best represent your answer for each statement >> To what extent do you believe that cognitive biases influence decision-making in the adoption of circular economy principles and practices?
biasesinfluencedecision-makingcirculareconomy::Agree	Agree	45		
biasesinfluencedecision-makingcirculareconomy::Neither agree nor disagree	Neither agree nor dis	9		
biasesinfluencedecision-makingcirculareconomy::Disagree	Disagree	1		
biasesinfluencedecision-makingcirculareconomy::Strongly Disagree	Strongly Disagree	2		
businessesprioritizesustainability::Strongly Agree	Strongly Agree	32	Availability	14. Please select the options below that best represent your answer for each statement >> To what extent do you believe that businesses should prioritize sustainability in their decision-making?
businessesprioritizesustainability::Agree	Agree	39		
businessesprioritizesustainability::Neither agree nor disagree	Neither agree nor dis	4		
businessesprioritizesustainability::Disagree	Disagree	2		
businessesprioritizesustainability::Strongly Disagree	Strongly Disagree	2		
changeHabits::No	No	1	Status Quo	7. Are you willing to change your habits to be more sustainable?
changeHabits::Yes	Yes	78		
climatechangecausedhumanactivity::Strongly Agree	Strongly Agree	31	Confirmation	14. Please select the options below that best represent your answer for each statement >> To what extent do you think that climate change is caused by human activity?
climatechangecausedhumanactivity::Agree	Agree	31		
climatechangecausedhumanactivity::Neither agree nor disagree	Neither agree nor dis	10		
climatechangecausedhumanactivity::Disagree	Disagree	5		
climatechangecausedhumanactivity::Strongly Disagree	Strongly Disagree	2		
econgrowthVSenviron::No	No	64	Sunk Cost	8. Do you think that the benefits of economic growth and development should outweigh the costs to the environment?
econgrowthVSenviron::Yes	Yes	15		
environfriendlychoices::Excellent	Excellent	6	Reference sustainability need	11. Please select the options below that best represent your answer for each statement >> How confident are you in your ability to make environmentally friendly choices in your daily life?
environfriendlychoices::Good	Good	31		
environfriendlychoices::Average	Average	30		
environfriendlychoices::Poor	Poor	12		
environfriendlychoices::Very Poor	Very Poor	0		
environproblemssolvedtechn::Strongly Agree	Strongly Agree	36	Availability	14. Please select the options below that best represent your answer for each statement >> To what extent do you believe that environmental problems can be solved through technology and innovation?
environproblemssolvedtechn::Agree	Agree	36		
environproblemssolvedtechn::Neither agree nor disagree	Neither agree nor dis	5		
environproblemssolvedtechn::Disagree	Disagree	1		
environproblemssolvedtechn::Strongly Disagree	Strongly Disagree	1		
increasedemand sustprod::Strongly Agree	Strongly Agree	24	Confirmation	14. Please select the options below that best represent your answer for each statement >> Do you agree with the following view: Is it imperative to reduce the use of fossil fuels in our daily lives, by increasing the demand for sustainable products?
increasedemand sustprod::Agree	Agree	37		
increasedemand sustprod::Neither agree nor disagree	Neither agree nor dis	12		
increasedemand sustprod::Disagree	Disagree	4		
increasedemand sustprod::Strongly Disagree	Strongly Disagree	2		
individualsactionimpactenviron::Strongly Agree	Strongly Agree	36	Confirmation	14. Please select the options below that best represent your answer for each statement >> Do you think it is important for individuals to take action to reduce their impact on the environment?
individualsactionimpactenviron::Agree	Agree	35		
individualsactionimpactenviron::Neither agree nor disagree	Neither agree nor dis	6		
individualsactionimpactenviron::Disagree	Disagree	1		
individualsactionimpactenviron::Strongly Disagree	Strongly Disagree	1		
informedsustainability::Excellent	Excellent	4	Reference sustainability need	11. Please select the options below that best represent your answer for each statement >> How informed are you about sustainability issues?
informedsustainability::Good	Good	30		
informedsustainability::Average	Average	38		
informedsustainability::Poor	Poor	7		
informedsustainability::Very Poor	Very Poor	0		
makechangeslifestyle::Very likely	Very likely	25	Anchor	12. Please select the options below that best represent your answer for each statement >> How willing are you to make changes to your lifestyle or consumption habits in order to support sustainability and protect the environment?
makechangeslifestyle::Somewhat likely	Somewhat likely	45		
makechangeslifestyle::Neither likely nor unlikely	Neither likely nor unl	6		
makechangeslifestyle::Somewhat unlikely	Somewhat unlikely	2		
makechangeslifestyle::Very unlikely	Very unlikely	1		
moremoneyforsustain::Very likely	Very likely	6	Sunk Cost	12. Please select the options below that best represent your answer for each statement >> Would you spend more money to buy repaired, re-used or recycled products than new ones?
moremoneyforsustain::Somewhat likely	Somewhat likely	26		
moremoneyforsustain::Neither likely nor unlikely	Neither likely nor unl	7		
moremoneyforsustain::Somewhat unlikely	Somewhat unlikely	23		
moremoneyforsustain::Very unlikely	Very unlikely	17		
nopropermannersustainablereality::Strongly Agree	Strongly Agree	7		
nopropermannersustainablereality::Agree	Agree	14		
nopropermannersustainablereality::Neither agree nor disagree	Neither agree nor dis	15		
nopropermannersustainablereality::Disagree	Disagree	30		
nopropermannersustainablereality::Strongly Disagree	Strongly Disagree	13		
policies::No	No	28	Self-serving	9. Do you believe that governments should take a more active role in promoting sustainability, even if it means limiting individual freedom of choice or imposing strict
policies::Yes	Yes	51		
reducesingle-useplastics?::Always	Always	3	Self-serving	13. Please select the options below that best represent your answer for each statement >> How often do you make an effort to reduce your carbon footprint or limit your use of single-use plastics?
reducesingle-useplastics?::Often	Often	34		
reducesingle-useplastics?::Sometimes	Sometimes	26		
reducesingle-useplastics?::Rarely	Rarely	12		
reducesingle-useplastics?::Never	Never	4		
societyenvirpractices::Strongly Agree	Strongly Agree	36	Availability	14. Please select the options below that best represent your answer for each statement >> Do you agree that it is important that society follows environmentally friendly practices?
societyenvirpractices::Agree	Agree	38		
societyenvirpractices::Neither agree nor disagree	Neither agree nor dis	2		
societyenvirpractices::Disagree	Disagree	1		
societyenvirpractices::Strongly Disagree	Strongly Disagree	2		
sustFocus::No	No	1	Reference sustainability	2. Do you believe sustainability should be focused on?
sustFocus::Yes	Yes	78		

Figure 142. Document groups and counts - Atlas.ti

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10. Appendix J – Vensim simulations

Figure 143. Equations and values of variables in Vensim for conceptual simulation of SFD

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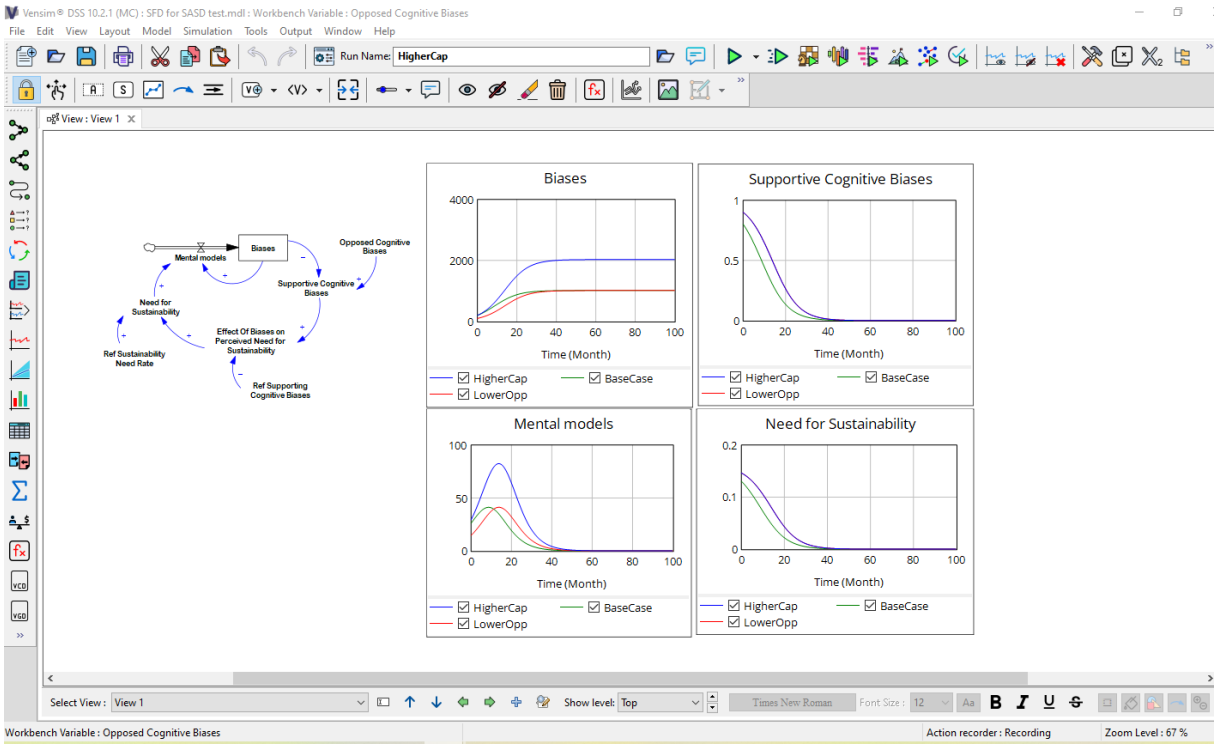

Figure 144. Vensim simulation screenshot for conceptual SFD simulation with survey data

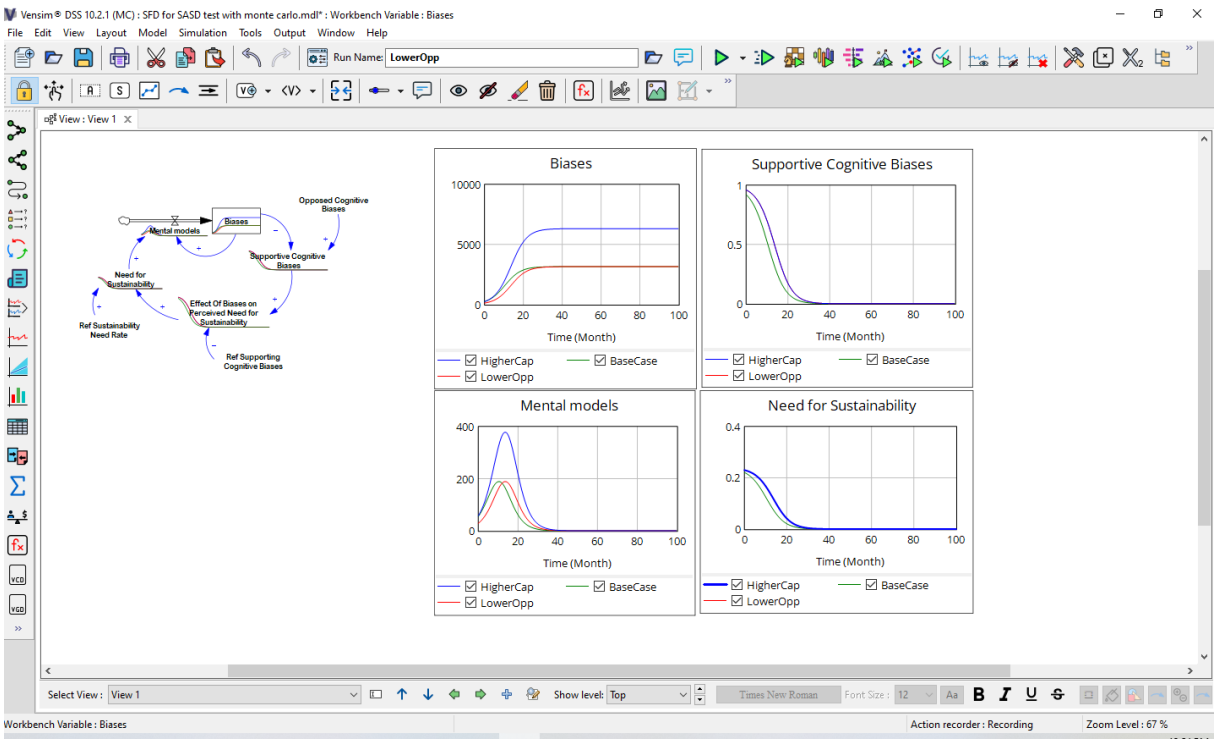

Figure 145. Vensim simulation screenshot for conceptual SFD with Monte Carlo data

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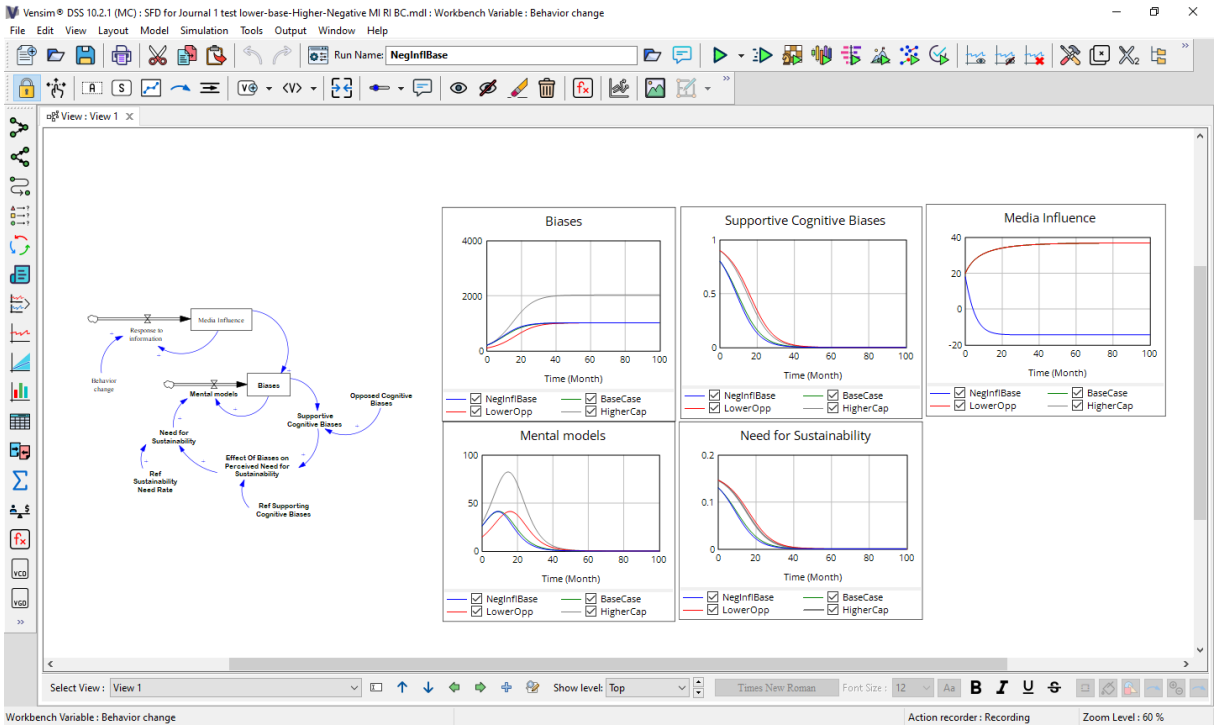

Figure 146. Vensim simulation screenshot for final integrated SFD simulation with survey data

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