Gordon Institute of Business Science
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Drivers and hindrances of technology adoption by manufacturing industries: A systematic literature review

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Philosophy (Evidence-Based Management).

05 December 2022

Abstract

Manufacturing is a core sector in the economy of a nation and currently faces increasing pressure to adopt highly sophisticated manufacturing technological innovations for competitiveness. This review examines the drivers and hindrances of adopting new manufacturing technological innovations within the industry 4.0 concept relative to context. Previous reviews lack an overall view of drivers and hindrances of industry 4.0 technologies adoption by manufacturing industries in developing and developed economy context. A systematic search of literature in the EBSCO and Science Direct databases between 2017 and 2022 resulted in 71 peer reviewed articles, followed by content analysis of gathered evidence to provide findings for this study. The identified six main drivers and seven hindrances of technology adoption as a result of integrating evidence from past studies contribute to literature. Added to that, the developed conceptual framework of technology adoption based on drivers and hindrances and their relationship to context, make another contribution to literature. The results revealed that corporate social responsibility, digital strategy, innovation, digitalisation maturity, competition, and customer demands are the six main drivers of technology adoption. Secondly, the results revealed that organisational constraints, funding, personnel-related issues, regulations and policy hindrances, technological issue, resistance to change, and lack of empirical evidence are the seven main hindrances of technology adoption. Moreover, results revealed that drivers and hindrances of technology adoption in a developing economy differ from a developed economy.

Keywords: drivers, hindrances, industry 4.0, technology adoption, manufacturing industry, industry 4.0

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Philosophy in Evidence Based Management at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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CHAPTER 1: INTRODUCTION

1.1. Introduction

This chapter discusses the introduction and background of the study, technology adoption definition, gap identification, study objective, problem statement and formulated research questions, selection of articles, contribution of systematic literature review, limitations of the study, and the conclusion.

1.2. Introduction and background

Technology has been evolving from first, second, third, and fourth revolutions. The invention of the steam powered manufacturing industries in the 18th century marked the emergence of the First Industrial Revolution that strategically dealt with dynamic business requirements and environmental factors (Adu-Amankwa et al., 2019; Jiang et al., 2022). The beginning of the 20th century experienced the introduction of the electricity powered production facilities coupled with the division of labour concept, marking the emergence of the second industrial revolution (Bhat et al., 2021; Jiang et al., 2022). The third industrial revolution emerged in the 1970s with the introduction of technologies like, computers, robots, and the Internet, which enhanced performance and productivity (Bhat et al., 2021; Strozzi et al., 2017). In recent years, manufacturing industries have been confronted with a wide range of highly sophisticated technological innovations referred to as industry 4.0 (14.0), and face increasing pressure to adopt them for competitiveness. Industry 4.0 or Fourth Industrial Revolution is a paradigm or composition of various innovative intelligent technologies such as, Internet of Things (IoT), artificial intelligence (AI), additive manufacturing (AM), blockchain, big data analytics (BDA) and autonomous robot (Azadi et al., 2021; Li et al., 2017; Machado et al., 2020; Mithas et al., 2022). Industry 4.0 is derived from the German term “Industrie 4.0” that was announced at the Hanover Fair in 2011 and emerged in 2013 as a German government initiative to increase the competitiveness of their manufacturing industries through the adoption of these innovative technologies (Dixit et al., 2022; Dohale et al., 2022; Kiel et al., 2017). Manufacturing is a system that involves material and information flow, converting materials into finished goods (Bi et al., 2021). Different decisions are made at different levels of information flow based on data collected from the manufacturing system, making it a highly complex process (Bi et al., 2021). The contribution by manufacturing to the prosperity of nations is significant (Ben-Daya et al., 2019). Considering the contribution by manufacturing industries to the prosperity of nations (Ben-Daya et al., 2019), it becomes imperative to adopt relevant technologies to create and maintain a superior position over competition (Dohale et al., 2022; Núñez-Merino et al., 2020; Parente et al., 2020; Ralston & Blackhurst, 2020), such that, other nations like European Union (EU), China and India have also taken the initiative to adopt the 14.0 technologies. For example, the Chinese government instituted “Made in China 2025” initiative to drive the adoption of 14.0 technologies by manufacturing, while India instituted the “Make in India” for the same initiative (Li et al., 2017; Luthra et al., 2020). On the other hand, EU invested $2.2 billion to support programmes for manufacturing technological advancements.

1.3. Definition of Technology Adoption (TA)

Technology adoption (TA) is a sociological model describing the process of adopting or accepting of an innovation or product relative to the adopting individual or organisation (Z. Xu et al., 2021). Another definition of technology by Blut and Wang (2020) is, putting technology to use for the purpose of benefiting from it. (Liang et al., 2021) defines technology adoption as implementation of new technology for the benefits that can be optimally drawn from it. There is a growing body of literature that recognises that the competitiveness of a firm is underpinned by the extent to which they adopt innovative technologies (Srivastava et al., 2022), to stay ahead of the pack. Faced with the need to promptly adapt to global environmental uncertainties, organisations need to develop frameworks that accommodate adoption of technologies at the right pace for competitiveness (Bag, Pretorius, et al., 2021). An accelerated pace of technology adoption results in greater investments and enhanced manufacturing activities as shown by a UK based review (Felsberger et al., 2022). The rapid emerging technologies (14.0) has led to increased studies on the technology adoption construct in various industries to motivate and improve the acceptance and use of these new technologies (Kurpjuweit et al., 2021; Z. Xu et al., 2021). With the aim of motivating technology adoption by individuals or organisations, studies on this topic have deviated from theories to applications (Z. Xu et al., 2021). Technology adoption has been applied in various fields such as farming and banking. For example, Beaman et al. (2021) developed frameworks to motivate technology adoption by farmers, using the theory of social learning, arguing that information friction may hinder technology adoption. While Dadoukis et al. (2021) established that banks that adopted high technologies prior to the COVID-19 crisis performed better through improved market returns and overall performance. However, the author of this paper defines technology adoption as embracing and using new, relevant, and aligned technologies at the right pace by organisations to efficiently compete, because it covers the main tenets of this study.

1.4. Gap identification

It is important to understand the key discussions and arguments on technology adoption, and how it has been reviewed to date since it has become pertinent for the manufacturing industry. For example, Naghshineh and Carvalho (2022) looks at how additive manufacturing (AM) technology adoption can impact supply chain resilience in different manufacturing industries. Naghshineh and Carvalho (2022) noted that the adoption of additive manufacturing technology is expected to improve the supply chain resilience. Machado et al. (2020) carried out a systematic literature review whose results allude to the fact that sustainable manufacturing is linked to the adoption of 14.0 technologies, insinuating that sustainability is a driver of technology adoption. Agrawal et al. (2022) gathered insights on progress and trends on the integration of Industry 4.0 technologies and the circular economy using systematic literature review and developed a framework that guides scholars and practitioners when assimilating industry 4.0 and circular economy. Similarly, the drivers and hinderances that will be highlighted by this review are intended to facilitate development of frameworks that guide and motivate organisations to adopt aligned technologies at the right pace. Another previously published study highlights barriers and enablers of technology adoption within the adoption process of 14.0 technologies and how they relate to different innovation types of outcomes (Stornelli et al., 2021). The review identified barriers and enablers of technology adoption and revealed the relationship between the categories of barriers and enablers and their link to innovation type outcomes, products, and processes (Stornelli et al., 2021). While existing literature reviews have identified drivers and hindrances of technology adoption focusing on sustainability, supply chain, innovation, or some of the 14.0 technologies, literature lacks an overall view of the drivers and hindrances of technology adoption for all the 14.0 technologies, all manufacturing industries, and how they relate to developed and developing economy contexts. Firstly, there is no consensus on what the drivers and hindrances of technology adoption are. Secondly, there is no conclusiveness on what drives and hinders technology adoption in a developing and developed economy contexts. These gaps need to be addressed so that drivers and hindrances of technology adoption are established to facilitate development of relevant frameworks that drive context specific adoptions. This study adopts 14.0 technologies outlined by (Zheng et al., 2021) as a full representation of all the technologies within the 14.0 framework (see table 1).

1.5. Study Objective

To overcome the knowledge gap on the lack of conclusiveness on what drives and hinders technology adoption, this study examines drivers and hindrances of technology adoption by manufacturing industries relative to context. The systematic literature review rationale is informed by two central weaknesses. Firstly, the need to identify drivers and hindrances of technology adoption for all the 14.0 technologies by manufacturing industries. Secondly, is the need to identify the drivers and hinderances of technology adoption by manufacturing industries in relation to context. The review outlines drivers and hinderances that relate to a developing economy and those that relate to the developed economy, separately. Although extensive research has been carried out on drivers and hindrances of technology adoption by manufacturing industries, no single study exists which looks at drivers and hindrances of 14.0 technologies adoption by all manufacturing industries relative to context. Table 1 shows a summary of the 14.0 technologies that inform this study and a description of each of them. This list includes, IoT, AI, AM, automation and industrial robotics, simulation, and modelling, augmented and virtual reality, blockchain, cloud technology, cyber-physical systems, and big data analytics (Zheng et al., 2021).

1.6. Problem Statement and Research question

The problem of this study is that drivers and hindrances for technology adoption are not well explained or known, thus forcing manufacturing companies to adopt technologies misaligned to their strategic objectives. Factors that drive and hinder technology adoption by manufacturing industries in a developing economy differ from a developed economy because they face different challenges (Hughes et al., 2022; Luthra et al., 2020; Tortorella & Fettermann, 2018; Vafadarnikjoo et al., 2021). For example, developed economies like German and Switzerland are leading the transition to 14.0 technologies, while developing economies lag (Hughes et al., 2022). At the same time, factors that drive and hinder technology adoption by manufacturing SMEs differ from large companies due to different strategies and different challenges (Kinkel et al., 2022; Mittal et al., 2020; Stornelli et al., 2021). For example, a German AI producer shows that the adoption of artificial intelligence (AI) in manufacturing industry for production purposes is 8% in SMEs and 26% in large companies (Seifert, 2018). It is important to document drivers and hindrances of technology adoption factors by context to facilitate development of frameworks that are context specific and provide relevant guidance and motivation for the adoption of indusrty 4.0 technologies as proposed by (Mittal et al., 2020; Moeuf et al., 2018; Prause, 2015; Vafadarnikjoo et al., 2021). Do these factors affect the pace of technology adoption? Do they even affect what technologies to adopt? Therefore, with a dearth of information, managers and other decision makers may be hindered from adopting relevant technologies for competitiveness and efficiency. A lack of information pertaining to which technologies to adopt, may cost the organisation or industry its growth, revenue generation prospects and productivity. This review will focus on the context of developing and developed economies only. A further analysis in the context of company size (SME and large) under developing and developed context is recommended for future reviews to provide guidance relevant for specific company size.

Research questions

Given the stated problem, the study interrogates the following formulated research questions:

RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?

RQ2 How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?

Figure 1 conceptualises the main aim of the systematic literature review.

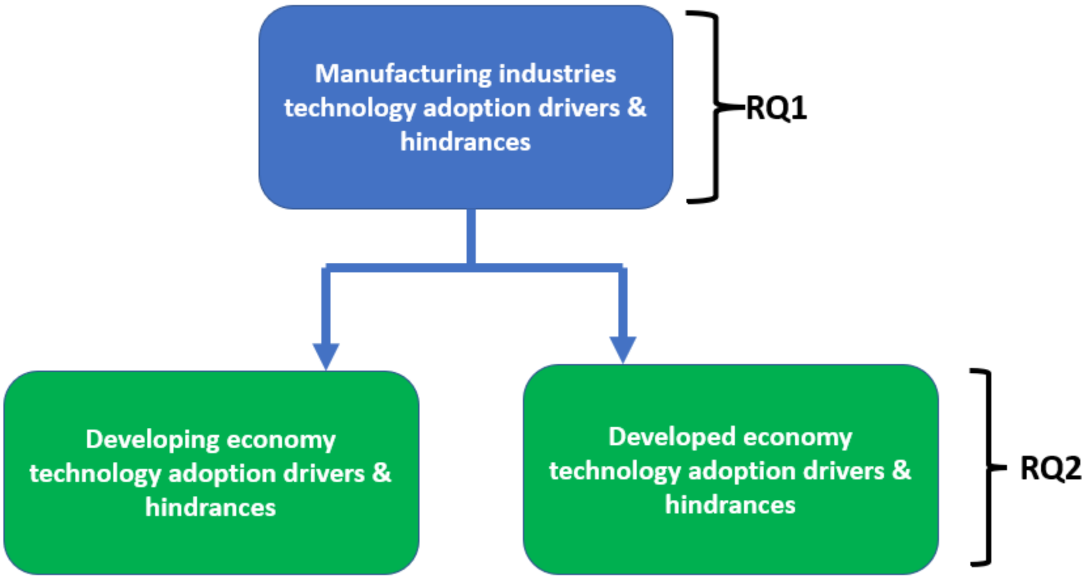

Fig 1: Conceptual framework

Table 1: listing of Industry 14.0 technologies adopted from Zheng et al. (2021

Technology	Description	Reference
Cyber-physical systems	CPS monitor systems and generate a virtual copy.	(Felsberger et al., 2022; Kiel et al., 2017; Kusiak, 2018; Laubengaier et al., 2022)
Internet of Things	IoT facilitates interaction of sensors and tangible objects like cars, machinery, etc.	;(Lee et al., 2018 ; Machado et al., 2020; Mithas et al., 2022; L. da Xu et al., 2018)
Big data analytics	BDA is the collection and analysis of large amount of data using multiple techniques.	(Cui et al., 2021; Ivanov et al., 2019; Kinkel et al., 2022)
Automation & industrial robots	A collaboration of robots, machines and huma beings on a shared platform.	(Ivanov et al., 2019; Machado et al., 2020; Mithas et al., 2022; Zheng et al., 2021)
Simulation & modelling	Enable design, creation, testing, and operating of systems virtually.	(Machado et al., 2020; Mourtzis, 2020; Núñez-Merino et al., 2020)
Cloud technology	Is a technology that provides storage electronically.	(Ben-Daya et al., 2019; Ghobakhloo, 2020; L. da Xu et al., 2018)
Blockchain	Is a secure digital distributed ledger.	(Govindan, 2022; Liang et al., 2021; Vafadarnikjoo et al., 2021; Zheng et al., 2021)
Augmented & virtual reality (visualisation technology)	An integration of technologies to create a virtual interactive platform for virtual objects.	(Moeuf et al., 2018; Mourtzis, 2020)
Artificial intelligence	A machine that is designed to function like a human being.	(Huber, 2021; Mithas et al., 2022; Toufaily et al., 2021)
Additive manufacturing	AM involves building layers in succession to produce customised designs.	(Kurpjuweit et al., 2021)

1.7. Articles selection criteria

It is evident from literature that the technology adoption construct has been recently studied extensively in the 14.0 technologies context, particularly the manufacturing industry. This study focuses on studies published between 2017 and 2022, where most of the 14.0 technologies studies were conducted. Given the evolving nature of technology, this review engaged with the current debates on the adoption of 14.0 technologies to identify the drivers and hindrances of technology adoption by manufacturing industries. To ensure collection of more credible and reliable evidence the study was based on 71 articles from top peer reviewed journals that are rated 3 and above according to the Association of Business Schools (ABS) listing. Chapter 2 provides more details of the articles selection criteria which includes the databases searched, keywords and the inclusion and exclusion criteria.

1.8. Contribution of the SLR

This review provides two main contributions to the body of literature. Firstly, the integration of evidence from past studies, resulting in the identification of drivers and hindrances of technology adoption in relation to context by manufacturing industries, contributes to the body of knowledge. Secondly, the developed conceptual framework for technology adoption based on drivers and hindrances, and how they relate to context, contributes to the body of knowledge as well.

1.9. Limitations of the study and directions for future research

The most important limitation for this systematic literature review lies in the fact that it was conducted by one person. Generally, multiple coders of data are engaged when conducting a systematic literature review to ensure interrater reliability of the study (Lombard et al., 2002). To manage this limitation, I coded the same data twice to ensure reliability of the findings (McHugh, 2012). Added to that I conducted the eligibility assessment twice to ensure selection of a credible final sample. A similar review can be conducted by more than one person, using a bigger sample size from multiple databases to ensure more credibility and reliability.

1.10. Synopsis of the SLR

This review is structured as illustrated in fig 2. In chapter 1, I discuss the rationale, problem, and research questions. In chapter 2 the method and analysis are discussed. Chapter 3 presents the literature review results. While chapter 4 discusses the literature review results. Lastly, chapter 5 discusses the research questions and the conclusion.

1.11. Conclusion

Having discussed the study rationale, problem, and research question, the following chapter discusses the methodology and analysis method followed. It provides a detailed discussion of the data collection and analysis process to demonstrate how the drivers and hindrance of technology adoption were identified.

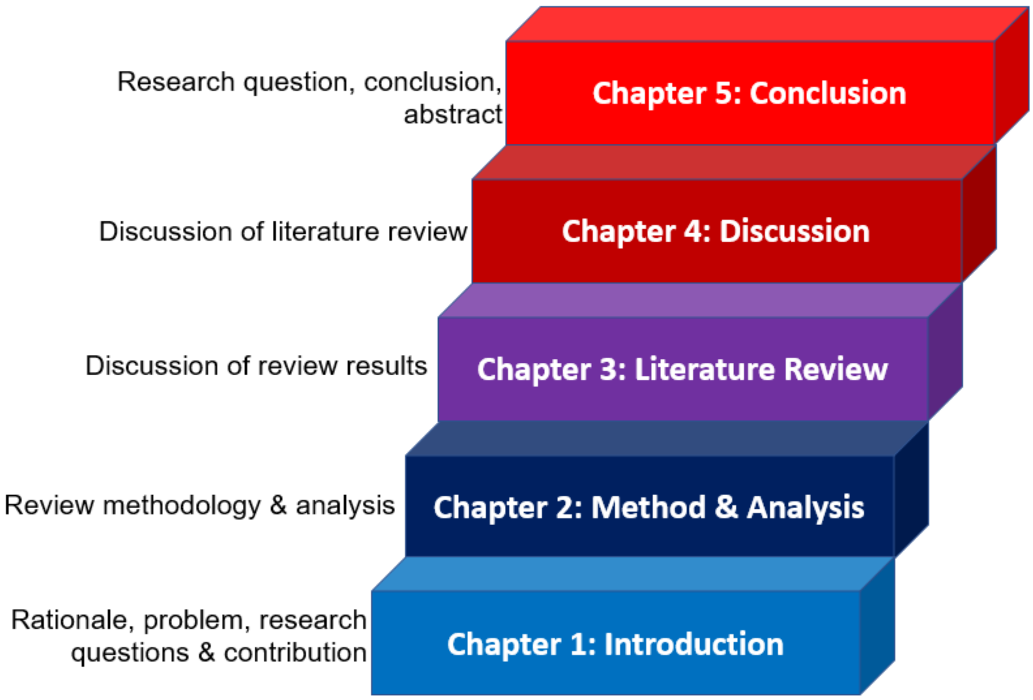

Fig 2: Process of systematic literature review

CHAPTER 2: METHOD AND ANALYSIS

2.1. Introduction

This section discusses the review method and the analysis. The review method provides details of the evaluation and selection of the sample. While the review analysis clearly articulates the content analysis process followed.

2.2. Review method

This review examines the drivers and hindrances of adopting new manufacturing technological innovations within the industry 4.0 concept in relation to different contexts. To achieve this, the review interrogates the following research questions:
RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?

RQ2 How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?

To answer the research questions, the selected structured review approach is the systematic literature review (SLR) methodology. The SLR method facilitates location, selection, and evaluation of contributions that have been made to a particular area of study (Núñez-Merino et al., 2020). It utilises existing peer-reviewed journal articles to explore clearly formulated research questions derived from a particular phenomenon (Agrawal et al., 2022; Denyer & Tranfield, 2009; Snyder, 2019; Vinodh et al., 2021). Snyder (2019) points out that the SLR method was initially utilised in medical science to systematically synthesise research findings. However, it is increasingly being utilised in social science research, enabling researchers to compare and synthesise data from different studies to identify gaps in the knowledge and guide future research (Vinodh et al., 2021). The other type of a structured review approach is the integrative literature review method which is used to critique and synthesise literature for the extension of knowledge and theory, making it unsuited for this study (Snyder, 2019). A semi-systematic literature review method is another type of a structured review approach which takes a narrative approach on the progress made in a particular area of research (Snyder, 2019). It does not follow a systematic review process, making it unsuited for this study (Snyder, 2019). Whereas the rationale for a SLR is to study past studies and analyse latest trend on a specific topic (Agrawal et al., 2022).

The author has identified some scholars that utilised the SLR to interrogate the concept of technology adoption, while other scholars primarily focused on the implications of technology adoption. For example, Naghshineh and Carvalho (2022) reviewed 87 peer-reviewed papers with the objective of examining the implications of additive manufacturing technology adoption through SLR. The authors established that additive manufacturing technology is anticipated to improve the supply chain resilience. On the other hand, Zamani (2022) employed SLR to review 349 peer reviewed journal articles to determine the dominant concepts on technology adoption in Small Medium Enterprises (SMEs). Zamani (2022) established that literature on technology adoption is fragmented, focusing on few categories of concepts. Zamani (2022) recommends the development of a technology adoption framework that aligns with infrastructure, regulations, strategy, and resources concepts, which have not been adequately research. Agrawal et al. (2022) sought to gather insights on progress and trends on the integration of industry 4.0 technology and the circular economy (CE) using SLR. The gathered insights facilitated the development of a framework that guides scholars and practitioners when integrating industry 4.0 and CE.

SLR synthesises research explicitly, following a clearly defined methodology that can be replicated (Denyer & Tranfield, 2009). High quality and credible evidence was utilised for this review to adequately inform the targeted audience (Denyer & Tranfield, 2009). I followed the PRISMA approach to identify eligible journal articles for the review (Moher et al., 2009). Preferred Reporting Items for Systematic Reviews (PRISMA) is an evidence-based approach that utilises a set of items to report in a systematic review meta-analysis (Moher et al., 2009). Stornelli et al. (2021) utilised the PRISMA approach to conduct a systematic literature review. The four stages in the PRISMA approach are, identification of articles, screening articles, full article assessment, and final review sample. Fig 3 shows the PRISMA chart for this review (Moher et al., 2009).

2.2.1. Identification of articles

Considering that database selection is the first step in conducting a literature search, it is important to ensure that articles are selected from reliable databases (Stornelli et al., 2021). To achieve this, EBSCO and Direct databases which are widely used and contain relevant peer reviewed articles were selected and used to identify articles.

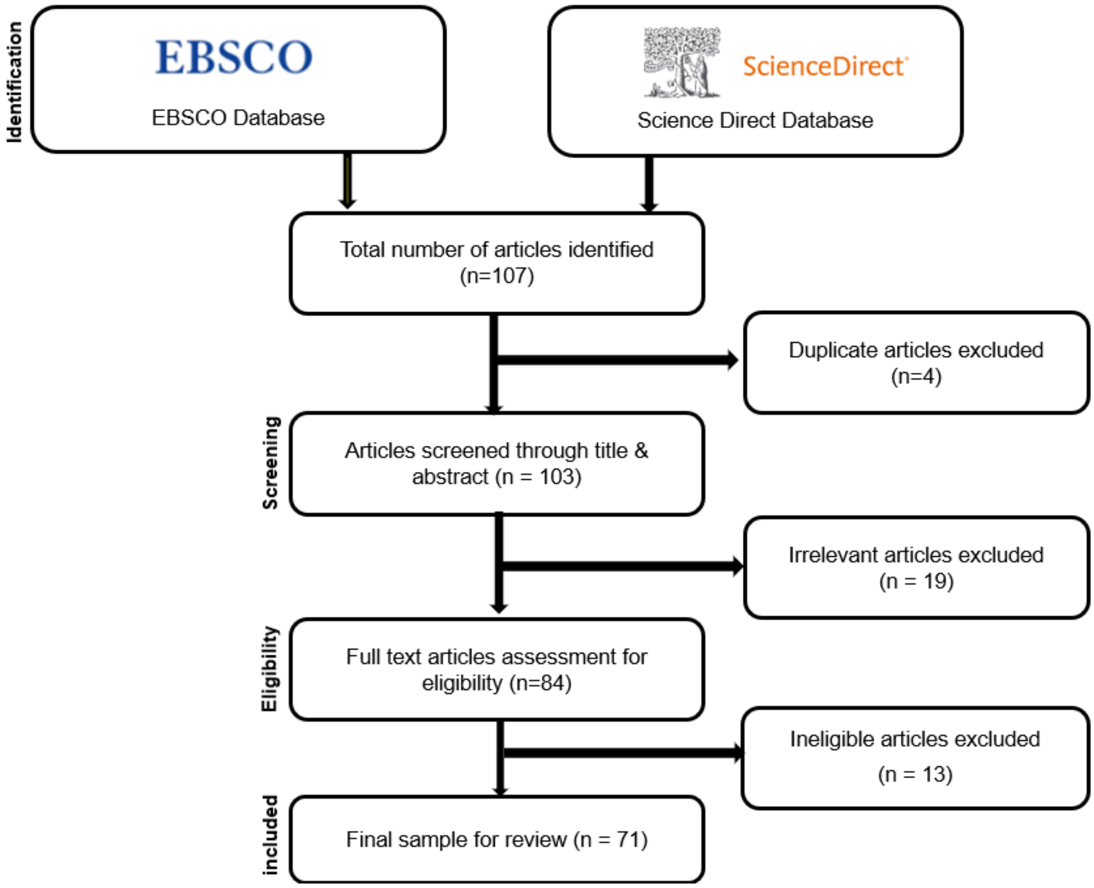

Fig 3: Systematic literature review articles flowchart

I selected articles for inclusion based on the inclusion criteria for this review. The inclusion criteria include peer reviewed articles from journals rated 3 and above according to the Association of Business Schools 2021 (ABS) academic journal guide, articles published between 2017 and 2022, and articles written in English language only. The exclusion criteria used constitutes journals that are rated below 3 on the ABS 2021 and conference proceedings. The journals identified as the suitable ones where most of the relevant articles are sitting are listed in Table 5 (see chapter 3) which shows the journals, journal rating, number of articles and the database. Table 5 shows that 16 journals drawn from two databases were used for this review. Other authors have been guided by the inclusion criteria and the search for articles was done using the selected keywords. Relevant keywords enable selection of relevant articles to address the research questions. The keywords selected for this review are technology adoption, manufacturing industry, industry 4.0, and drivers and hindrances. Past reviews on technology and manufacturing have identified eligible articles using a three-level query (Osterrieder et al., 2020; Stornelli et al., 2021). I applied these three query levels: contextual (manufacturing and production), technological (technology, industry 4.0, Internet of Things, smart), analytical (adoption). Fig 4 shows the combinations applied to the topic, abstract and keywords of the articles identified.

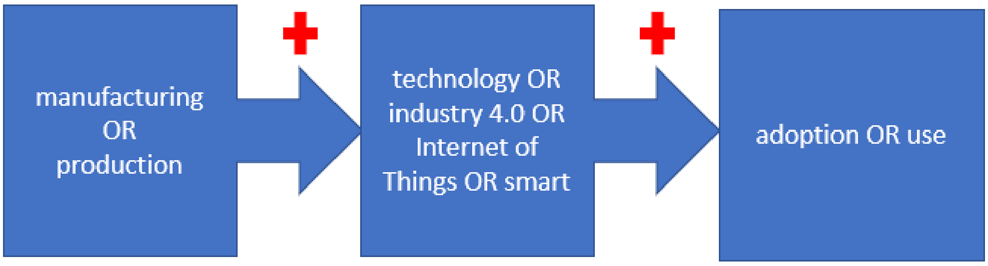

Fig 4: The three query levels

Utilising the above-mentioned keywords, inclusion, and exclusion criteria, I identified 107 articles. From the identified 107 articles, 4 articles were duplicates from the two bases utilised. EBSCO and Science Direct. The 4 articles were excluded, and 103 articles underwent further screening which is outlined in section 2.2.

2.2.2. Screening of articles

Following the PRISMA framework in fig 3, screening of articles follows the identification of articles. The screening of 103 articles entailed examination of the title, abstract and keywords. This step facilitated establishing whether the identified articles were relevant to address the research questions. From the 103 articles screened, 19 articles were found to be irrelevant to address the research questions and were excluded, resulting in 84 articles. The section below describes how the 84 articles were further examined for eligibility.

2.2.3. Eligibility assessment

In line with (Weng et al., 2010) I assessed the 84 articles that remained after the screening process. This process entails identifying ineligible articles and excluding them from the review. The remaining eligible articles represent the final sample that is analysed. For the eligibility assessment, I conducted full-text reading of the 84 articles to determine whether they presented relevant evidence to address research question 1 (drivers and hinderances of technology adoption) and research question 2 (how drivers and hindrances relate to context). I included empirical studies and review articles that presented evidence on technology adoption drivers and hindrances of 14.0 technologies by the manufacturing industry. I excluded articles that presented evidence on the adoption of 14.0 technologies without discussing drivers and hindrances, as well as articles that discussed 14.0 technologies in other contexts that are not manufacturing.

After assessing the 84 articles, 13 articles were found to be ineligible and were excluded, resulting in a final sample of 71 articles. Since this review was conducted by one person, the author settled for a sample size of 71 to ensure validity of the study. Naghshineh and Carvalho (2022) employed 87 articles and Agrawal et al. (2022), employed 165 articles, where researchers participating were more than one. Section 2.2.4 discusses the final sample and the steps that follow.

2.2.4. Final sample

The final sample for this review is 71 articles and was reached after careful identification, screening, and assessment of the articles. The selection and evaluation of the articles was conducted by one author. To minimise the single researcher bias I conducted the eligibility assessment twice (Durack & Wieland, 2017). For the first eligibility assessment I read the abstracts, theoretical frameworks, findings, and conclusions of the 84 articles. The first eligibility assessment resulted in the exclusion of 6 articles and the remaining articles were 78. The second eligibility assessment involved the full-text reading which resulted in the exclusion of 7 articles and a final sample of 71 articles was reached. The final sample of articles was exported to a reference management system, Mendeley software to organise and automatically generate the bibliography and eligibility assessment (Sau & Bhakta, 2018).

Table 4 (see chapter 3) presents the final sample for the review by number of articles and the respective methodology and analysis is provided in section 3.1.2. Table 5 (see chapter 3) shows the final sample for the study by journal, journal rating, database, and the number of articles per journal by percentage. Detailed analysis of the journal assessment is provided in section 3.1.3. Table 2 lists the literature review (conceptual methodology) articles in the sample that are related to the technology adoption, manufacturing, and industry 4.0. It shows the author, study perspective, analysis period, number of review articles and the respective keywords. Section 2.2 of this chapter discusses the analysis of the final sample of 71 articles. An analysis of the characteristics of published SLRs in table 2 shows that none of them provides an overall view of drivers and hindrances of adopting 14.0 technologies in the manufacturing industries relative to context. Added to that, this study focuses on all the manufacturing industries within the business management spectrum.

Table 2: Reviews related to technology adoption, manufacturing, and industry 4.0

Author	Perspective	Analysis period	No. of article	Keywords
Agrawal et al. (2022)	Industry 4.0 within Circular Economy	2011- 2020	165	artificial intelligence, bibliometric analysis, Circular Economy, environmental policy, Industry 4.0, resource efficiency, sustainable societies
Ben-Daya et al. (2019)	Internet of things and supply chain management	2008 - 2017	166	Internet of Things (IoT); supply chain management; industry 4.0; supply chain processes; smart supply chain
Bittencourt et al. (2021)	Industry 4.0 triggered by Lean Thinking	2011 - 2019	33	Lean Production; Lean Thinking; Industry 4.0; Smart factory; 4th industrial revolution
Dohale et al. (2022)	52 Years of manufacturing strategy	1969 - 2021	1034	Manufacturing strategy; evolutionary review; thematic analysis; systemic framework; future research agenda
Ghobakhloo (2020)	Digital technology and smart manufacturing	2014 - 2019	165	Industry 4.0; smart manufacturing; manufacturing digitalisation; industrial internet
Guan et al. (2019)	Production research at 55	1960 - 2015	8653	clustering; temporal aggregation; literature review; topics over time; latent semantic analysis
Huber et al. (2022)	Industry 4.0-an information systems capability perspective.	2009 - 2019	42	Industry 4.0, Fourth industrial revolution, Information systems capabilities, Capability framework
Jiang et al. (2022)	Production scheduling and Industry 4.0.	2012 - 2017	10	Production scheduling; Industry 4.0; centralised scheduling; distributed scheduling; decentralised scheduling; cloud manufacturing scheduling
Khorram et al. (2017)	Additive manufacturing management	1990 - 2014	123	advanced manufacturing technology; manufacturing management; manufacturing strategy; additive manufacturing; co-citation analysis
Liao et al. (2017)	Past, present and future of Industry 4.0	2012 - 2016	224	the fourth Industrial revolution; Industry 4.0; systematic literature review; qualitative research; quantitative research; research
Machado et al. (2020)	Sustainable manufacturing in Industry 4.0	2008 - 2018	35	sustainable manufacturing; Industry 4.0; 4th industrial revolution; literature review; industrial development agenda
Mithas et al. (2022)	Artificial intelligence and industry 4.0	1983 - 2020	463	Industry 4.0, Operations, Supply Chain Management, Artificial Intelligence (AI), Information Technology (IT), Business Excellence, Strategy, Governance, Digital Transformation
Moeuf et al. (2018)	SMEs in the era of Industry 4.0	2011 - 2016	80	production control; Industry 4.0; smart manufacturing; operational improvement; SME; SMB
Mourtzis (2020)	Manufacturing systems	2010 - 2018	744	manufacturing systems; simulation; information and communication technologies; digitalised manufacturing; review
Naghshineh et al. (2021)	Additive manufacturing technology adoption for supply chain	2006 - 2021	87	Additive manufacturing, Supply chain resilience, Literature review, Propositions, Framework, Research agenda
Neumann et al. (2021)	Industry 4.0 and the human factor.	2014 - 2019	646	Human factors, Ergonomics, Industry 4.0, Digital transformation, Content analysis, System design

Continued - Table 2: Reviews related to technology adoption, manufacturing, and industry 4.0

Author	Perspective	Analysis period	No. of article	Keywords
Núñez-Merino et al. (2020)	Industry 4.0 and Lean supply chain	1996 - 2019	78	: Lean Supply Chain Management; Industry 4.0; Information and Digital Technologies; Systematic Literature Review
Osterriede et al. (2020)	The smart factory as a key construct of industry 4.0	2007 - 2017	100	Smart factory Smart manufacturing Industry 4.0 Internet-of-Things Big data Literature review
Parente et al. (2020)	Production scheduling in the context of Industry 4.0	2010 - 2019	97	scheduling; production planning; Industry 4.0; industry challenges; two-stage literature
Piccarozzi et al. (2022)	Industry 4.0 and sustainability	2012 - 2021	192	Industry 4.0 Sustainability Pillars Management Systematic literature review
Rad et al. (2022)	Industry 4.0 and supply chain performance	2005 - 2021	221	Industry 4.0 Supply chain Digitization Digitalization Digital technologies Literature
Rosin et al. (2020)	Industry 4.0 technologies on Lean principles	2009 - 2019	85	Industry 4.0; lean management; capability levels
Stornelli et al. (2021)	Advanced manufacturing technology adoption and innovation	1999 - 2019	87	advanced manufacturing, technological adoption, adoption process, innovation types, barriers and enablers, Industry 4.0
Strozzi et al. (2017)	Smart Factory	2007 - 2016	467	systematic literature review; Industry 4.0; smart factory; citation network; co-word
Xu et al. (2021)	Technology adoption	1973 - 2020	11706	Technology adoption Bibliometric analysis Novel technology Top-cited papers
Yang et al. (2021)	Adoption of digital technologies in supply chains	2005 - 2019	55	Digital technology, Digital supply chain, Digitalization Technology adoption, Supply chain management
Zheng et al. (2021)	Application of Industry 4.0 in manufacturing	2015 - 2019	186	Industry 4.0; manufacturing systems; advanced manufacturing technology; manufacturing processes; smart manufacturing; literature review
Zhou et al. (2022)	Production and operations management for intelligent manufacturing	2005 - 2020	73	Intelligent manufacturing; production and operations management; value creation mechanisms; resource configuration and capacity planning; production planning; scheduling; logistics

2.3. Review analysis

2.3.1. Introduction

I present a content analysis of the literature on technology adoption to address research question 1 (*RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?),* to identify drivers and hindrances of 14.0 technologies adoption which have been included in literature as of now. Research question 2 (*RQ2 How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?)* further examines drivers and hindrances of technology adoption relative to context. This review provides two main contributions to the body of literature. Firstly, the integration of evidence from past studies, resulting in the identification of drivers and hindrances of technology adoption in relation to context by manufacturing industries. Secondly, the developed conceptual framework for technology adoption based on drivers and hindrances, and how they relate to context, contributes to the body of knowledge as well. Content analysis enables systematic analysis of past studies to address research questions, as well as identify research gaps (Grosse et al., 2017). This characteristic of content analysis method enabled answering research question 1 and achievement of the first contribution to the body of knowledge. Another important characteristic of the content analysis is that it is used to develop a framework that conceptually describes the phenomenon under study (Elo & Kyngäs, 2008) . The second contribution to literature, mentioned above, which entails development of a conceptual framework for technology adoption was achieved by utilising this characteristic of content analysis.

Content analysis approach involves a code frequency count, based on the assumption that the code with more frequency count indicate that it is an emerging theme (Stemler, 2000). Besides making inferences based on the frequency count alone, content analysis enables the pulling out of full sentences or phrases where the keyword is coming from, so that objective conclusions are drawn out of the data (Weber, 1990). This strengthens the validity and replicability of the inferences being made from the data (Stemler 2000), which made it a good fit for the analysis of this review. However, some scholars do not find content analysis as a credible approach for analysing data because they say that a high frequency count of a keyword does not necessarily mean that a concept or a theme is important (Weber, 1990). Even though some scholars do not find content analysis as a credible approach, it has recently been used extensively in business management studies (Neuendorf, 2017). Another commonly used method for data analysis by social science researchers is thematic data analysis. Thematic analysis is a qualitative data analysis tool used to identify and code emerging themes in qualitative data (Dapkus, 1985). This method is most suited to analyse data collected from the semi-structured interviews and observations because it will enable identification of emerging themes from the interviewees' responses (Braun & Clarke, 2012), hence not selected for this review.

While content analysis is a robust data analysis approach which is systematic and replicable technique that is used to compress large volumes of data into fewer categories based on clearly defined coding rules, there are two identified weaknesses that tear down the utilisation of content analysis. These weaknesses are that wrong definitions of categories and non-mutually exclusive and exhaustive categories can jeopardise the analysis results (Grosse et al., 2017). Despite these limitations, content analysis effectively analyses data in a systematic way, highlighting key research findings as well as identification of research gaps (Grosse et al., 2017). Since a systematic literature review systematically synthesises and compares data from different studies to identify gaps in research and recommend future research (Agrawal et al., 2022), I selected the content analysis approach because it facilitates for a systematic and objective way of drawing out conclusions that can be used to identify research gaps and recommend future research.

Content analysis can be used to analyse quantitative or qualitative data deductively or inductively (Elo & Kyngäs, 2008). I employed the inductive content analysis approach to enable description of the phenomenon and identify the drivers and hindrances of adopting 14.0 technologies (Hsieh & Shannon, 2005). The inductive approach enables exploration of new fields of study (Terry et al., 2017) and technology adoption in the context of 14.0 technologies is a relatively new area of study and is fragmented (Zamani, 2022). On the other hand, deductive approach is best suited to explain a field of study and is suited for quantitative studies (Clarke & Braun, 2017). Unlike the deductive approach which tends to direct the analysis towards the author's interests and presumptions, inductive analysis does not attempt to fit the analysis into the author's interests or assumptions when coding (Braun & Clarke, 2006). It seeks to identify codes and themes from the data set (Braun & Clarke, 2006). Neumann et al. (2021) employed the content analysis approach on SLR to count specified keywords in a sample, following the assumption that a high frequency count on a keyword suggests that it is important. Similarly, I utilised the qualitative software ATLAS ti 9 to carry out codes and code groups creation from the selected sample data.
Section 2.3.2 discusses in detail the process followed to conduct the content analysis.

2.4. Content analysis process

The inductive content analysis process followed the preparation, organising and reporting phases (Elo & Kyngäs, 2008). The reporting phase presented the analysis results in form of conceptual model and tables (Elo & Kyngäs, 2008). The content analysis phases are discussed in detail in the following sections 2.4.1, 2.4.2 and 2.4.3.

2.4.1. Preparation phase

In the preparation phase, manufacturing company was selected as the unit of analysis (Elo & Kyngäs, 2008). A unit of analysis is selected to established what to analyse (Elo & Kyngäs, 2008). This review analyses drivers and hindrances of technology adoption by manufacturing companies within the manufacturing industries. It further analyses the drivers and hindrances of technology adoption by manufacturing industries relative to context. In section 2.4.2, the organising phase is discussed. Another important element of the preparation phase involves familiarisation of the data by the researcher through reading it several times (Elo & Kyngäs, 2008). The author thoroughly engaged with data several times to adequately prepare for the analysis process.

2.4.2. Organising phase

The organising phase involved three steps. These steps are open coding, grouping codes and categorising (Elo & Kyngäs, 2008). A code is a word or a short phrase that designates an important meaning to words or visual data (Cooper, 2009). Codes are components that are used to build a code groups (themes) (Clarke & Braun, 2017). Code groups are created to classify the codes that describe them narrowly (Dey, 1993). The code groups are further narrowed down to categories. Open coding is a process of creating codes while reading text to capture aspects of the content (Elo & Kyngäs, 2008). To come up with the code book, the final sample of 71 articles was exported into ATLAS ti 9 software. The following steps adopted from (Hwang, 2008) were followed in ATLAS.ti 9 for the coding process:

Step 1: Open coding – codes were created in ATLAS ti 9 while reading each article in the sample. The coding process utilised ATLAS.ti 9, a qualitative data analysis software widely utilised by researchers to record and process, to identify, and code themes that are emerging from data (Hwang, 2008). Open coding was guided by the research questions that were formulated to identify drivers and hindrances of technology adoption relative to context. A total of 88 codes which are linked to sentences and phrases from the articles were created. Table 9 presents the listing of the codes and the respective code count. For example, “Sustainability practices” code frequency count is 15, while “Coercive pressure” code frequency count is 4. Based on the assumption that the code with a higher frequency count indicates that it is an emerging theme (Stemler, 2000), it can be inferred that “Sustainability practices” is an emerging theme that is studied more than “Coercive pressure”. Besides making inferences based on the code frequency count alone, full sentences or phrases where the code is coming were pulled out, so that objective conclusions are drawn out of the data (Weber, 1990). This strengthened the validity and replicability of the inferences being made from the data (Stemler 2000). Appendix 1 shows the code report generated which illustrates the codes and the sentences and phrases linked to them. After creating the codes, step 2 followed.

Step 2: Grouping codes - A code book was created by narrowing down codes in step 1 into code groups to determine the key themes for the drivers and hindrances of technology adoption. A code book is a listing of all code groups and the associated codes (Dey, 1993).Themes are derived from code groups that have been generated by identifying codes that are related (Ryan & Bernard, 2003). Grouping codes reduces the number of codes identified in step 1 to enable adequate description of the phenomenon to generate knowledge (Elo & Kyngäs, 2008). Through interpretation of the codes, the author made decisions as to which codes to put in the same code group (Elo & Kyngäs, 2008). A total of 34 code groups were created in ATLAS ti 9 (see Appendix 2). These code groups were further analysed outside ATLAS ti 9 and narrowed further down to 19 code groups. The 17 code groups were categorised as either drivers or hindrances. A total of 10 drivers and 7 hindrances were categorised accordingly. The reporting phase discussion follows in section 2.4.3.

2.4.3. Reporting phase

Following the detailed analysis in the organising phase, four tables (see table 6, 7, 8 and 10) and two figures (see fig 7 and 8) were created to illustrate the analysis findings. Table 6 lists the top 25 words in the keywords of the 71 articles and the respective occurrence number. Table 7 presents the code groups (themes) and codes for the identified drivers of technology adoption. Table 8 presents the code groups (themes) and codes for the identified hindrances of technology adoption. While table 10 presents the drivers and hindrances relative to context. Fig 7 presents the keyword cloud generated from ATLAS ti 9. Fig 8 presents the framework developed that illustrates the drivers and hindrances relative to context (developing and developed economy). A more detailed discussion on the tables, keyword cloud, and framework is provided in chapter 3.

2.4.4. Intra-rater reliability test

To ensure inter-rater reliability of a study, multiple coders are engaged to measure the extent to which they evaluate the same data and code it the same way (Lombard et al., 2002). While intra-rater reliability measures the extent to which one person evaluates the same data multiple times at different times and code it the same way (McHugh, 2012). Given that this review was conducted by one author, intra-rater reliability test was conducted to measure the reliability of the study. I coded the same data twice over a period of five weeks. In week one I coded the data for the first time, and in week five I coded the same data for the second time. An intra-rater reliability test was conducted to ensure reliability. I conducted coding on six pre-defined codes on the sample of 71 articles within five weeks. The coding was compared using ordinal numbers, 0 and 1). The number 1 represented coding was done the same way, while zero represented the coding was done differently. The intra-rater results in table 3 below, show an 83% agreement, indicating the reliability of the coding.

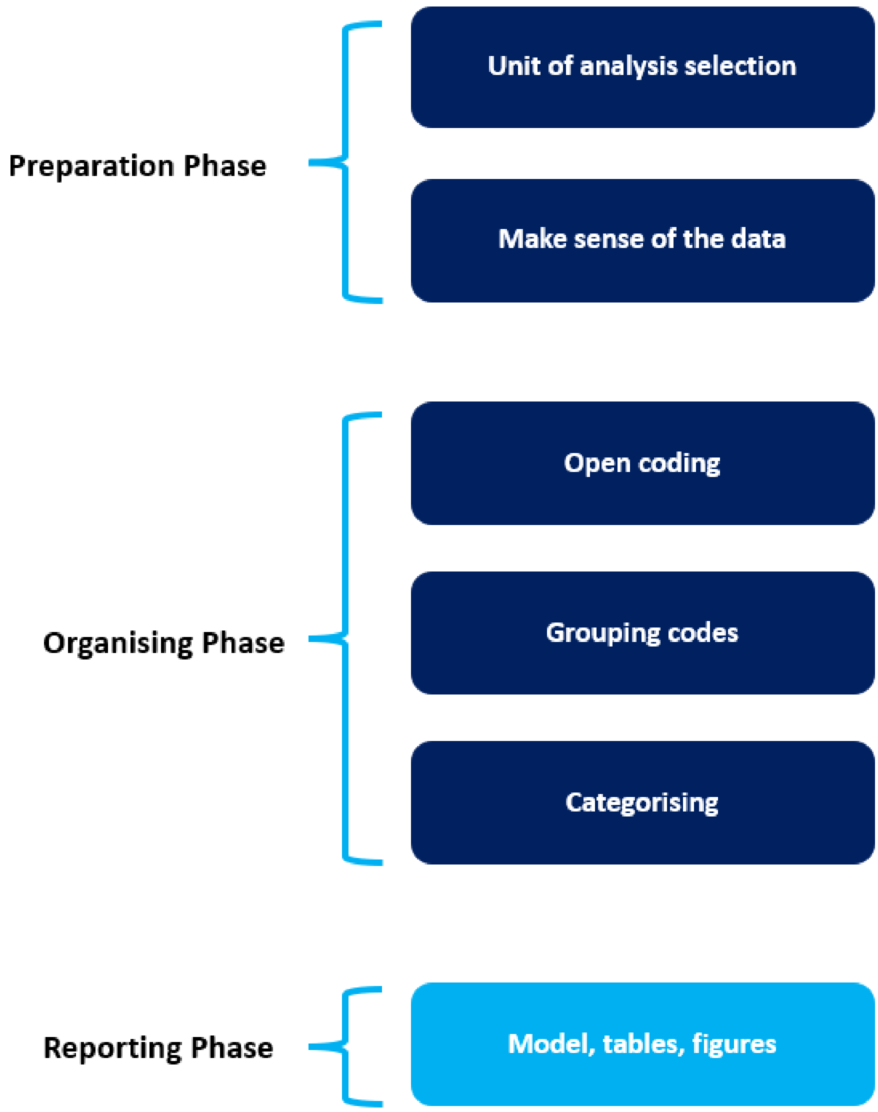

Fig 5: Content analysis process

Table 3: Intra-rater results

Code No.	**First time coding**	**Second time coding**	**Difference**
1	1	1	0
2	1	1	0
3	1	1	0
4	0	1	1
5	1	1	0
6	1	1	0
No. of Zeros			5
No. of items			6
% Agreement			**83%**

2.5. Conclusion

A rigorous process of articles selection and analysis produced results that are presented in the following section, chapter 3. The identified drivers and hindrances of technology adoption relative to context are presented to address the formulated research questions.

CHAPTER 3: STRUCTURED LITERATURE REVIEW

3.1. Introduction

This chapter presents and discusses the results of the systematic literature review. I provide the descriptive analysis of the literature on technology adoption by manufacturing industries, summary of the review objective, discussion of the identified drivers, discussion of the identified hindrances, and finally, a discussion of the drivers and hindrances relative to context.

RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?

RQ2 How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?

3.2. Descriptive analysis of literature

I selected a sample size of 71 articles after screening and assessing the identified 107 articles. Presentation of number of articles by year of publication, methodology assessment, journal assessment, and keyword statistics is discussed in this section.

3.2.1. Number of articles by year of publications

A chronological analysis of the number of articles by year of publication was carried to show the literature the author engaged with. Fig 6 shows the number of articles by year of publication. From fig 6, it shows that the author engaged most with current debates on technology adoption because 19 articles (26.76%) which show the highest representation of the sample were published in 2022. This is followed by 18 articles (25.35%) which were published in 2021. Considering the evolving nature of technology, it is crucial to engage with current debates to ensure the relevance of the study. Another point to note is that the number of studies published on the adoption of 14.0 technologies in the context of manufacturing has gradually risen over the past 3 years (70%) of the articles). The logical explanation to this recent gradual rise in these publications is the need to build resilience by organisations for uncertainties like COVID-19 crisis, which can be addressed by these new technological advancements (Dadoukis et al., 2021).

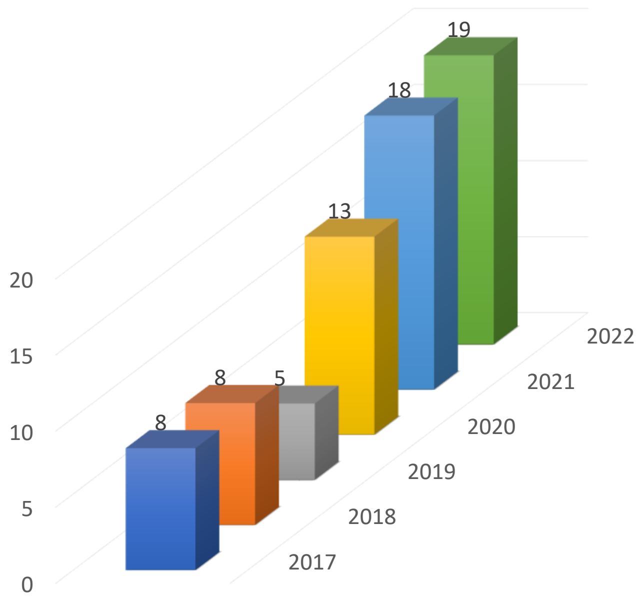

Fig 6: Number of articles by year of publication

3.2.2. Methodology assessment

The methodology employed on articles in the sample was analysed by methodology and number of articles. Conceptual, quantitative, qualitative, and mixed methods methodologies form part of the review sample. Table 4 shows that conceptual methodology studies are most common with a 39% representation. Quantitative methodology studies follow with a 38% representation. Thirdly, are the qualitative methodology studies with an 21% representation. Lastly, mixed methods methodology studies have a 1% representation. Conceptual studies are focused on developing conceptual frameworks using past studies evidence and do not have empirical content (Núñez-Merino et al., 2020). Quantitative studies generally make use of statistical techniques like regressions, simulations, structural equation, among others (Núñez-Merino et al., 2020). Qualitative studies employ case studies (Saunders, 2016). While mixed methods combine qualitative and quantitative methods (Saunders, 2016).

Table 4: Methodology assessment

Methodology	Number of articles	%
Conceptual	28	39%
Mixed Methods	1	1%
Qualitative	15	21%
Quantitative	27	38%
Total	71	100%

3.2.3. Journal assessment

The number of articles published by journal was analysed as well. Table 5 shows that the sample was drawn from total 16 journals. International Journal of Production Research journal, which is rated 3, published the highest number of articles on technology adoption of 14.0 by manufacturing industries with a 55% (39 articles) representation. Technological Forecasting and Social Change has 8 articles (11%). International Journal of Production Economics has 4 articles (6%). Technovation journal and Production Planning and Control both have 3 articles (4%). Business Strategy and the Environment, Information Management, and Information Systems Frontiers have 2 articles (3%). 8 journals have 1 article (1%). The 71 analysed articles appear in a total of 16 journals, and they are all rated 3 and above according to ABS academic journal guide. It also shows that 73% (52 articles) of the final sample was extracted from the EBSCO database, while 27% (19 articles) was extracted from ScienceDirect database.

3.2.4. Keywords statistics

Analysis of keywords helps to determine the keywords that are used the most by different authors on specific areas of study (Agrawal et al., 2022). Table 6 shows the top 25 frequently used words in keywords in technology adoption and manufacturing industry studies. Figure 7 presents a word cloud of the most frequently used words in keywords in the technology adoption and manufacturing industries studies.

From table 6 and fig 7 it shows that the most frequently used words in keywords are manufacturing, industry 4.0, supply, chain, technology, adoption, smart, internet, innovation, data, digital, sustainability, sustainable, blockchain, lean, things, production, scheduling, industrial and management. Manufacturing has the highest count of 56 occurrences, followed by industry 4.0. Supply, chain, technology, and smart follow, to list the 7 top highest words.

Table 5: Journal assessment

Journal	Journal rating	Journal Quartile	Journal Index	No. of articles	%	Database
Annals of Operations Research	3	Q1	111	1	1%	EBSCO
Business strategy and the environment	3	Q1	115	2	3%	EBSCO
California Management Review	3	Q1	139	1	1%	EBSCO
Industrial Marketing Management	3	Q1	147	1	1%	ScienceDirect
Information & Management	3	Q1	170	2	3%	ScienceDirect
Information Systems Frontiers	3	Q1	73	2	3%	EBSCO
International journal of operations & production management	4	Q1	146	1	1%	EBSCO
International Journal of Production Economics	3	Q1	197	4	6%	ScienceDirect
International Journal of Production Research	3	Q1	153	39	55%	EBSCO
Journal of Business Logistics	3	Q1	85	1	1%	EBSCO
Journal of Management Information Systems.	4	Q1	153	1	1%	EBSCO
Production and Operations Management	4	Q1	120	1	1%	EBSCO
Production Planning & Control	3	Q1	85	3	4%	EBSCO
Research Policy	4*	Q1	255	1	1%	ScienceDirect
Technological Forecasting and Social Change	3	Q1	134	8	11%	ScienceDirect
Technovation	3	Q1	140	3	4%	ScienceDirect
Total				**71**	**100%**	

Table 6: Top 25 words used in the keywords used in the manufacturing technology adoption and industry 4.0

Word	Occurrences	Length	%
manufacturing	56	13	6.31%
industry	51	8	5.63%
4.0	50	3	5.40%
supply	25	6	2.81%
chain	24	5	2.70%
technology	23	10	2.59%
smart	17	5	1.91%
management	16	10	1.80%
systems	15	7	1.69%
review	14	6	1.58%
literature	12	10	1.35%
adoption	11	8	1.24%
industrial	11	10	1.24%
internet	11	8	1.24%
lean	11	4	1.24%
things	10	6	1.13%
data	9	4	1.01%
digital	9	7	1.01%
innovation	9	10	1.01%
production	9	10	1.01%
research	9	8	1.01%
scheduling	9	10	1.01%
blockchain	8	10	0.90%
sustainability	8	14	0.90%
sustainable	8	11	0.90%

Fig 7: The word cloud of words used in the top keywords in the selected articles (Colour figure can be viewed in ATLAS.ti 9 software)

3.3. Summary of the review objective

I synthesised the findings to understand how the identified drivers and hindrances of technology adoption by manufacturing industries relate to context. Different contexts present different needs, hence, the need to develop frameworks specific to context (Tortorella et al., 2019). The derived themes connect the 71 articles that have been synthesised. Fig 8, table 7, and table 8 show the results of the identified themes relative to context. The analysed contexts are developing economy and developed economy. Table 7 shows 10 identified technology adoption drivers that are linked to 36 codes. While table 8 shows seven identified themes (code groups) of technology adoption hindrances that are linked to 35 codes. From the sample, 12 articles (17%) discuss technology adoption of I4.0 relative to contexts, developing economies, developed economies, SMEs, and large companies (Bag, Pretorius, et al., 2021; Cugno et al., 2022; Govindan, 2022; Hughes et al., 2022; Kinkel et al., 2022; Luthra et al., 2020; Mittal et al., 2020; Moeuf et al., 2020; Tortorella et al., 2019; Vafadarnikjoo et al., 2021). While trying to understand factors that drive and hinder technology adoption in different contexts of the manufacturing industries, I noted that different contexts have adopted different types of I4.0 technologies for various reasons. For example, European SMEs have significantly adopted IoT sensors and laser scanners to efficiently plan for production (Mittal et al., 2020). From the I4.0 technologies basket, some SMEs have strategically selected technologies that are relevant for their operation, a move that other manufacturing companies might want to consider. There is however a dearth of studies that provide technology adoption framework specific to SMEs to guide the adoption process (Mittal et al., 2020). This has resulted in manufacturing industries missing opportunities to realise increased productivity, efficiency, and revenue. However, for this review, the developing and developed economy contexts are the ones being analysed. A further analysis of SMEs and large companies within a developed and developing economy is recommended for future research.

3.4. Drivers of technology adoption

From the synthesis of the findings, 10 drivers were identified. These drivers are corporate social responsibility, digital strategy, innovation, competition, government support, management support, digitalisation maturity, customer demands, improved research and development, and good corporate Image. To adopt new technology, organisations analyse why, how, and what. When analysing why, organisations are looking at the purposes that drive technology adoption (Yang et al., 2021). While the how, focuses on the process and method of technology adoption (Yang et al., 2021). Lastly, what, analyses the possible outcomes and impacts of technology adoption (Yang et al., 2021). A driver is a resource, process or condition that facilitates necessary adoptions for growth (Luthra et al., 2020). Technology adoption looks at customer demands (Bag, Pretorius, et al., 2021; Ghobakhloo, 2020; Kinkel et al., 2022). It is important for organisation to ensure customer demands are met to stay ahead of the pack (Bittencourt et al., 2021). Technology adoption considers what competitors are doing to maintain a superior position (Bag, Pretorius, et al., 2021; Kamble et al., 2020; Kinkel et al., 2022; Luthra et al., 2020). It also looks at organisational vision and strategy for alignment to achieve set goals (Moeuf et al., 2018; Parente et al., 2020; Yang et al., 2021). Organisations seek to establish benefits associated with technology adoption which include, enhanced efficiency, flexibility, risk optimisation, achievement of sustainability practices or competitiveness, to mention a few (Bittencourt et al., 2021; Ivanov et al., 2019; Kinkel et al., 2022; Machado et al., 2020; Mittal et al., 2020).

Informed by the conceptual framework in fig 8, analysis of drivers and hindrances of technology adoption show that a contextualised approach is necessary, given that drivers and hindrances differ from one context to the other. For example, while German manufacturing industries in a developed economy do not experience hindrances like lack of funding, personnel related issue or lack of government support, developing economies experience them and need to find a way to overcome them and adopt relevant technologies.

From the 10 identified technology adoption drivers, six are regarded the main drivers because of the highest frequency code counts and the analysis of the sentences and phrases linked to them (see table 9). These six drivers are corporate and social responsibility, digital strategy, innovation, digitalisation maturity, competition, and customer demands. According to table 9 which provides a listing of codes and the respective code counts frequency, sustainability practices (15), competitive priorities (13), customisation (10), smarter decisions (8), innovation initiatives (7), integration capabilities (5), competition (4), and pressure from customers (3), have the highest counts that are linked to the 6 drivers, implying their importance as they form part of the most frequent debates in literature. This section will discuss findings on the 10 themes (drivers) that were identified after analysing the drivers code book, drivers code count and the code report. Table 7 lists the drivers (code group and respective codes), Table 9 lists drivers code count, and Appendix 1 shows part the code report. The actual code report is 63 pages long. Appendix 1 displays 1 page of the 63 pages of the code report which shows that a total of 88 codes were created and some of the code quotations that were used to analyse data to draw out contextual meaning so that meaningful conclusions are made. The 6 main drivers of technology adoption are discussed first in section 3.4.1., followed by the 4 secondary drivers of technology adoption discussion in section 3.4.2. The 4 secondary drivers are government support, management support, improved research and development, and good corporate image.

3.4.1. Main drivers of technology adoption

Corporate social responsibility

Other studies examine corporate social responsibility. Organisations that prioritise adherence to sustainability practices and safety are more likely to adopt 14.0 technologies to achieve set goals (Agrawal et al., 2022; Cui et al., 2021; Dixit et al., 2022; Goathood, 2020; Hughes et al., 2022; Jiang et al., 2022; Mittal et al., 2020; Piccarozzi et al., 2022). Sustainability practices code has the second highest code count after flexibility, reflecting its importance in the current literature debate. Corporate social responsibility integrates existing organisational business frameworks to enhance manufacturing industries' relationships with their key stakeholders which include, customers, suppliers, employees, the environment, and global communities (Ghobakhloo, 2020). Evidence shows that corporate social responsibility polices that regulate and safeguard social, economic, and environmental sustainability practices are expected to drive adoption of 14.0, since these technologies are expected to enable alignment to the set policies (Ghobakhloo, 2020).

Digital strategy

The existence of a digital strategy within an organisation is expected to significantly enable the adoption of 14.0 technologies (Bittencourt et al., 2021; Laubengaier et al., 2022; Luthra et al., 2020; Moeuf et al., 2018; Parente et al., 2020; Theorin et al., 2017; Yang et al., 2021). Strategic priorities, customisations, development of dynamic environments capabilities, smarter decision-making priorities inform the digital strategy of an organisation which significantly enable adoption of technologies (Laubengaier et al., 2022; Parente et al., 2020).

Innovation

The analysed sample articles show that innovation priorities are closely linked to the organisational vision and strategy and that it extensively influences technology adoption (Bag, Pretorius, et al., 2021; Mithas et al., 2022). An organisation that prioritises innovation for a competitive edge, adopt new technologies drive innovative initiatives. Innovative initiatives are mostly linked to strategy and in some studies are analysed under the strategy driver (Wamba & Queiroz, 2022). Innovation is perceived to be the only way to attain and maintain a competitive advantage by organisations (Dixit et al., 2022).

Digitalisation maturity

Technology adoption in developed economies like Germany and Switzerland is mainly driven by digitalisation maturity (Azadi et al., 2021; Bittencourt et al., 2021; Ghobakhloo, 2020; Hughes et al., 2022; Srivastava et al., 2022; Yang et al., 2021). Digitalisation maturity is summarised by the existence of digital competences, integration capabilities, openness to change, smart factory culture, apt technological infrastructure, and cybersecurity maturity (Azadi et al., 2021; Bittencourt et al., 2021; Mithas et al., 2022; Yang et al., 2021). The existence of these enabling capabilities in developed economies automatically facilitate fast-paced technology adoption which is required in highly dynamic technological environments (Hughes et al., 2022; Luthra et al., 2020; Mourtzis, 2020; Tortorella & Fettermann, 2018). Because of digitalisation maturity in most developed economies, they possess the agility required to respond quickly to changing and are generally open to change (Ghobakhloo, 2020; Moeuf et al., 2020). Cybersecurity maturity drives technology adoption by manufacturing industries (Mithas et al., 2022; Vafadarnikjoo et al., 2021). Technology adoption presents data security concerns, and some organisations avoid adoption of some technologies (Ghobakhloo, 2020; Toufaily et al., 2021). To address this concern, organisations need to develop and achieve cybersecurity maturity to avoid any limitations that are associated with data insecurities (Toufaily et al., 2021). Data security is one of the main concerns when organisations are making decisions to adopt technology. Blockchain technology adoption enables organisations to develop the necessary cybersecurity maturity that drives adoption (Govindan, 2022; Kurpjuweit et al., 2021; Liang et al., 2021; Mithas et al., 2022; Toufaily et al., 2021; Vafadarnikjoo et al., 2021; Wamba & Queiroz, 2022). Blockchain is a distributed ledger technology that guarantees authenticity of digital information, allowing organisations to manage ownership of data (Kurpjuweit et al., 2021; Liang et al., 2021; Mithas et al., 2022). It provides enhanced transparency and traceability in supply chain management, with high visibility of inventory movements, increasing operational efficiency (Ghobakhloo, 2020; Khorram Niaki & Nonino, 2017; Kiel et al., 2017; Mithas et al., 2022; Núñez-Merino et al., 2020).

Competition

Competition is another important technology adoption driver in the form of institutional pressure, increased pressure from competitors, the specific industrial sector that a company belongs to, and coercive pressure (Bag, Gupta, et al., 2021; Kamble et al., 2020; Kinkel et al., 2022; Luthra et al., 2020; Yang et al., 2021). Pressure from competitors that adopt new technologies for enhanced efficiency, drive technology adoption by manufacturing industries. To avoid loss of market share or business closure, organisations adopt new technologies as well to effectively compete (Bag, Gupta, et al., 2021; Luthra et al., 2020). For example, Kamble et al. (2020) found that Indian manufacturing companies have been coerced to adopt new technologies because of the intensified pressure to effectively compete.

Customer demands

Customer demands, though fairly discussed in the sample, are one of the main drivers of technology adoption. Customer demands involve customer satisfaction, which puts organisations under pressure to achieve to retain them (Mithas et al., 2022; Parente et al., 2020; Yang et al., 2021). Manufacturers are facing increased demand from customers to meet their varied tastes and preferences of products at a relatively fast rate (Bag, Gupta, et al., 2021). The continued demands from customers involve complicated products that can only be met by highly advances technologies like 14.0, thereby positively influencing adoption (Kinkel et al., 2022).

3.4.2. Secondary drivers of technology adoption

Government support

A relatively small percentage of sample articles focused on government support. Government support as a driver of technology adoption summarises the initiatives by government to fund and organise technology adoption programmes, training programmes, and policies that influence and motivate adoption of new advanced technologies to benefit the manufacturing industries (Kinkel et al., 2022; Liao et al., 2017; Luthra et al., 2020; Srivastava et al., 2022). For example, the French government initiated a digital transformation review called “La Nouvelle France Industrielle” in 2013 to formulate policies that drive aoption of cutting-edge technologies (Liao et al., 2017). On the other hand, South Korean government presented the “Innovation in Manufacturing 3.0) in 2014 to strategically transform their manufacturing digitally in accordance with 14.0 (Liao et al., 2017). While the Singapore government rolled out a “Research, Innovation and Enterprise” initiative in 2016 to spearhead advanced manufacturing technologies adoption (Liao et al., 2017).

Management support

Management support was fairly discussed in the sample, and it entails the relevant support from top management to adopt new technologies, as well as effective human resources management policies that facilitate identification and internal training of competent skills to drive digital transformation (Bag, Gupta, et al., 2021; Felsberger et al., 2022; Stornelli et al., 2021). The top management leadership style that creates a conducive environment for adoption in terms of favourable corporate culture, corporate governance and enabling policies provides the required management support for technology adoption (Stornelli et al., 2021). Organisations in the manufacturing industries are pressured to stay abreast with new technological advancements such that it becomes imperative for management to train and search for competent skills that can champion digital transformation (Felsberger et al., 2022; Stornelli et al., 2021).

Improved research and development

Improved research, development, and implementation for future technological advancements by organisations act as a powerful strategic planning tool that is likely to drive technology adoption at an increased pace (Ghobakhloo, 2020; Kinkel et al., 2022). Another important element of the research and development is the development of capabilities to conduct internal adequate research on technology before implementation to avoid adoption of underutilised or irrelevant technology (Moeuf et al., 2020). Manufacturing industries need to prioritise the research and development element to adopt technology and the right pace and effectively compete.

Good corporate image

Lastly, organisations are pressured to imitate technologies that have adopted by other organisations to keep up with the market drifts (L. Zhou et al., 2022). Adopting new technology is expected to enhance the image of an organisation, such that other companies adopt new technologies for a better reputation (Liang et al., 2021; Zhou et al., 2020).

While analysing the drivers of technology adoption, the researcher noted that codes benefits are benefits of technology adoption had been coded as drivers. However, a close analysis at the sentences and phrases linked to these codes, resulted in excluding these identified benefits from the drivers' list. Some of these benefits are flexibility, enhanced efficiency, increased revenue, and increased productivity. Other authors discuss how these perceived benefits are a by-product of drive technology adoption

(Laubengaier et al., 2022; Piccarozzi et al., 2022). Looking at the benefits, they can motivate technology adoption, which can potentially drive adoption.

3.5. Hindrances of technology adoption

Technology adoption can be hindered due to various factors which need to be identified and overcome to enable adoption (Stornelli et al., 2021). Table 8 provides a listing of the identified seven hindrances (themes) of technology adoption in the manufacturing industries. These seven hindrances are organisational constraints, personnel-related issues, regulations and policy hindrances, resistance to change, technological issues, lack of empirical evidence, and high cost of capital. The seven hindrances are linked to 36 codes. Challenges, difficulties, and disadvantages associated with a specific technology, hinders its adoption. Table 9 provides a listing of the hindrances and drivers code count frequencies, of which, the higher the code count frequency the more important the code or challenge is (Stemler, 2000). Table 9 shows that, lack of 14.0 technologies champion, has the highest frequency code count on the hindrances, insinuating that it is the main challenge that hinder technology adoption, according to the sample. Lack of 14.0 technologies champion challenge is linked to the organisational constraints hindrance (theme). The second highest code frequency count is, difficulties in integrating new processes code, which is also linked to the organisational constraints theme (challenge). The third highest code frequency count is difficulties in creating business case code, which is also linked to the organisational constraints hindrance (theme). Following the content analysis notion that high frequency count insinuates the importance of the code, which subsequently mean the importance of the theme that it is linked to (Stemler, 2000), organisational constraints emerge as the main hindrance. Evidence from the sample shows that organisational constraints has been discussed the most by sample studies and needs to be overcome.

Organisational constraints

Organisational constrains theme is associated with lack of technologies champion, new processes integration difficulties, and business case development difficulties (Buer et al., 2021; Ghobakhloo, 2020; Kamble et al., 2020). Lack of 14.0 technologies champion speaks to the absence of a relationship between technological investments and productivity economic benefits (Buer et al., 2021; Govindan, 2022; Kamble et al., 2020). Lack of informed analysis of technology adoption investment and the associated benefits has emerged as the major challenge hindering technology adoption. Organisations need to develop technologies champion and efficiently compete. Technologies champion is closely linked to difficulties in integrating new processes. Generally, adoption of new technologies involves integration of new processes (Kamble et al., 2020). If an organisation does not have capabilities to integrate new processes linked to new technology, adoption maybe hindered (Ghobakhloo, 2020; Govindan, 2022; Hughes et al., 2022; Kamble et al., 2020; Laubengaier et al., 2022; Liang et al., 2021; Xu et al., 2018). It is important for an organisation to establish the importance and relevance of technology prior adoption (Toufaily et al., 2021). However, inability to justify and motivate for technology adoption hinders adoption (Buer et al., 2021; Ghobakhloo, 2020; Stornelli et al., 2021; Toufaily et al., 2021). These three discussed challenges are constraints that need to be addressed at organisational level to enable technology enable.

Funding

Funding required for technology adoption may hinder adoption. According to table 9, financial constraints code, has the fourth highest code count frequency and is linked to the high cost of capital theme (hindrance). High cost of capital theme summarises the technology infrastructure cost, high technology adoption costs, and system adaptation sunk costs (Kiel et al., 2017; Margherita & Braccini, 2020; Stornelli et al., 2021). Added to the technological infrastructure costs is costs associated with the implementation and training costs, which are high as well (Huber, 2021). Another significant cost linked to technology adoption is sunk costs (Huber, 2021). Sunk costs include engaging expertise that is required to facilitate formulation of digital vision and strategy prior to adoption (Huber, 2021). It is important for organisations to accurately determine the financial investments required to adopt technology and adequately plan for relevant technological projects.

Personnel-related issues

As organisations adopt new technology, personnel-related issues may arise (Huber, 2021; Moeuf et al., 2020). These issues include challenges to train seasoned managers to lead the adoption, job automation constraints with unionised companies, and lack of skills to drive technology adoption (Ghobakhloo, 2020; Huber, 2021; Kusiak, 2018; Laubengaier et al., 2022; Margherita & Braccini, 2020; Moeuf et al., 2020; Srivastava et al., 2022). Organisations need to train seasoned managers to who can handle highly technological projects, which may present financial resources and time challenges for organisations (Huber, 2021; Laubengaier et al., 2022; Moeuf et al., 2020). Another challenging element of technology revolution is the potential loss of jobs as business and manufacturing processes get automated, leaving employees at a risk of losing jobs (Ghobakhloo, 2020; Kusiak, 2018; Margherita & Braccini, 2020). Companies that belong to unions that protect the interests and rights of employees, tend to experience resistance from unions to adopt new technology, to ensure that there is no job loses (Margherita & Braccini, 2020). Technology adoption studies discuss lack of skills as one of the main hindrances of adopting 14.0 technologies like AI, IoT, AM (Agrawal et al., 2022; Ben-Daya et al., 2019; Ben-Nerd & Siemsen, 2017). Organisations that do not face resistance from unions to adopt new technologies, simply fail to find the right skills required to adopt 14.0 technologies. (Bag, Pretorius, et al., 2021; Ghobakhloo, 2020; Huber, 2021; Srivastava et al., 2022).

Regulations and policy hindrances

Regulations and policy hindrances can hinder technology adoption by manufacturing industries. These impediments include, lack of government support, lack of information, lack of legislation, and lack of standardisation (Ben-Ner & Siemsen, 2017; Govindan, 2022; Huber, 2021; Stornelli et al., 2021; Vafadarnikjoo et al., 2021). Past studies show that government support in terms technology adoption initiatives significantly drive adoption (Liao et al., 2017; Luthra et al., 2020). Other governments like China, Switzerland, and Germany took initiatives to drive adoption of 14.0 technologies and the results indicate increase in adoptions (Hughes et al., 2022; Liao et al., 2017; Luthra et al., 2020; Yang et al., 2021). At governmental and organisational level, it is important to facilitate dissemination of information related to any new technologies to ensure adoptions. Lack of information has resulted in slow paced or non-adoption (Huber, 2021). Also, lack of legislation for technology may hinder adoptions (Govindan, 2022). Legislation guides adoption of technologies (Govindan, 2022). For example. Blockchain technology require government legislation to address adoption issues (Govindan, 2022). Closely related to lack of legislation is lack of standardisation. Lack of standardisation is the absence of general and standard guidance for the implementation of technology (Govindan, 2022). Technology like blockchain require standardisation because of the security issues that it presents (Govindan, 2022). Standardisation is a tough and challenging task, which, if note done, hinders technology adoption (Govindan, 2022; Stornelli et al., 2021).

Technological issues

New technology is bound to present technological issues or challenges for organisations. The main technological issues that were derived from the sample have to do with integration and automation and limited automation (Ghobakhloo, 2020; Govindan, 2022; Hughes et al., 2022; Kiel et al., 2017). Integration issues emanate from lack of skills to drive the integration or incompatible existing technology that cannot be integrated with new technology (Ghobakhloo, 2020; Govindan, 2022; Stornelli et al., 2021). Automating business or production processes may result in system disruptions, that present operational and financial risks (Stornelli et al., 2021). At the same time, technological issues may be because of automation limitations in terms of inadequate infrastructure (Hughes et al., 2022; Stornelli et al., 2021).

Resistance to change

Technology adoption maybe resisted by employees who are not willing to change the way they do their work (Cui et al., 2021; Govindan, 2022; Kusiak, 2018; Margherita & Braccini, 2020). The transition from an existing technology to a new technology may be a challenge for organisations because it may involve learning new the technology and job losses (Margherita & Braccini, 2020). If employees are not ready for the change, the adoption maybe hindered.

Lack of empirical evidence

Lastly, lack of empirical evidence may hinder technology adoption (Cugno et al., 2022; Kiel et al., 2017). Some manufacturing companies are not aware of the implications and effects 14.0 technologies because empirical studies are not conclusive, providing contradicting evidence (Kiel et al., 2017). The benefits and challenges of these new technologies are presented in a contradicting way by practitioners, researchers, consultants, and politicians, which may hinder adoption. Therefore, there is need for more empirical studies that provide conclusiveness on the 14.0 technologies to enable adoptions.

Table 7: Technology adoption drivers

Drivers (Themes/ Code groups)	Sub-categories (Codes)	Authors
Corporate social responsibility	Circular economy Lean practices Safety Sustainability practices Fewer raw materials Sustainable production	Agrawal et al 2022; Cui et al 2021; Dixit et al 2022; Hughes et al 2022; Jiang et al 2022; Mittal et al 2020; Picarrozi et al 2022 Bag et al 2021, Ben-Ner &Soemse 2017
Digital strategy	Competitive priorities Customisation Increased dynamic business environments Cybersecurity maturity Optimise risk Smarter decisions Effective crisis management Knowledge management Strategic priority	Bittencourt et al 2021; Laubengaier et al 2022; Luthra et al 2020 Parente et al 2020; Moeuf et al 2018; Toufaily et al 2021 Mithas et al 2022 Theorin et al 2017; Yang et al 2021 Cheng et al 2022; Cugno et al 2022; Kinkel et al 2022
Innovation	Innovation initiatives	Bag et al 2021; Mithas et al 2022
Competition	Competition Industrial sector Institutional pressures Coercive pressure	Bag et al 2021; Kable et al 2020; Luthra et al 2022; Yang et al 2021 Kinnkel et al 2022
Government support	Government support Technology adoption programmees Training programmes	Kinnkel et al 2022; Luthra et al 2022 Liao et al 2017; Srivastava et al 2022
Management support	Management of human resources policies Senior management support	Felsberger et al 2022; Stornelli et al 2021
Digitalisation maturity	Digital competences Digital maturity Integration capabilities Openness to change Smart factory culture Technological infrastrucure	Azadi et al 2021; Bittencourt et al 2021; Ghobakhloo et al 2022 Luthra et al 2022; Srivastava et al 2022; Yang et al 2021
Customer demands	Improved customer satisfaction Pressure from customers Product complexity	Bag et al 2021; Kinkel et al 2022; Ghobakhloo et al 2022
Improved research and development	Improved research and development	Ghobakhloo et al 2022
Good Corporate Image	Better business reputation	Liang et al 2021; Zhou et al 2022

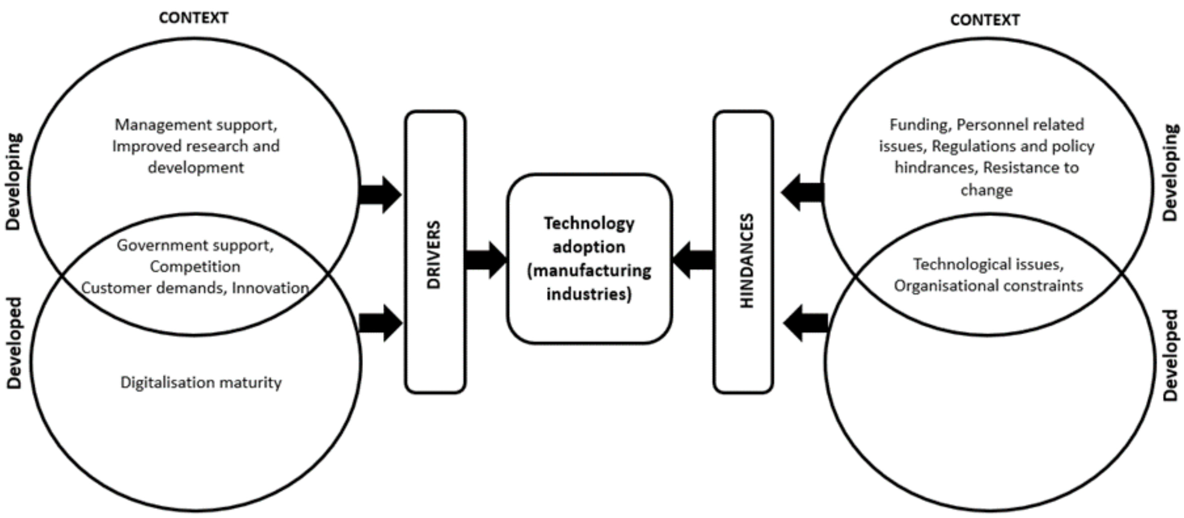

Fig 8: Drivers and hindrances of technology adoption relative to context

Table 8: Technology adoption hindrances

Code Groups (Themes)	**Codes**	**Authors**
Personnel-related issue	Challenge to train seasoned managers Job automation constraints within Lack of big data analysis competencies Lack of skills by manufacturing sector Reticence from executives Skills development issues	Huber et al 2022; Kusiak 2018; Ghobakhloo et al 2022; Laubengaier et al 2022; Srivastava et al 2022 Kusiak 2018;
Regulations and policy hindrances	Lack of government support Lack of information Lack of legislation Lack of standardisation	Huber et al 2022; Govindan 2022; Liang et al 2021 Vafadarnikjoo et al 2021
Resistance to change	Workforce resistance to change	Cui et al 2021; Govindan 2022
Technological issues	Difficulties in data integration Limitation of automations Limited automation Data security constraints Lack of awareness of data security Lack of trust with system vendors Uncertainty of technological needs Threat to intellectual property	Ghobakhloo et al 2022; Hughes et al 2022; Kinkel et al 2017 Mithas et al 2022; Govindan 2022 Felsberger et al 2022; Huber et al 2022; Liang et al 2021
Organisational constraints	Difficulties in creating business case Difficuties in integrating new processes Lack of 14.0 technologies champion Unfavourable culture values Lack of common smart factory values Lack of implementation plan Lack of business model raodmap Lack of corporate governance Lack of management support Difficulties in long-term planning of Lack of contextualised advanced technologies criteria	Buer et al 2021; Liang et al 2021; Kurpjuweit et al 2021; Xu et al 2018; Laubengaier et al 2022; Dasgupta & Gupta 2019 Dohale et al 2022 Touaily et al 2021 Mithas et al 2022; Stornelli et al 2022 Felsberger et al 2022; Chen et al 2022; Bittencourt et al 2021
Lack of empirical evidence	Lack of empirical evidence	Cugno et al 2022
Funding	Cost of IT infrastructure Financial constraints High costs Sunk costs of system adaptation	Ben-Daya et 2019; Huber et al 2022; Margherita & Bracinni 2020 Mithas et al 2022; Stornelli et al 2022

Table 9: Code count listing

	Code (Driver)	Code Count
1	Flexibility	16
2	Sustainability practices	15
3	Competitive priorities	13
4	Improved productivity	10
5	Customisation	10
6	Smarter decisions	8
7	Decentralisation	7
8	Innovation initiatives	7
9	Cost reduction	7
10	Increased revenue	7
11	Enahnced supply chain performance	6
12	Senior management support	6
13	Enhanced efficiency	5
14	Improved quality	5
15	Strategic priority	5
16	Integration capabilities	5
17	Supply chain visibility	4
18	Circular economy	4
19	Competition	4
20	Coercive pressure	4
21	Constant unit cost	4
22	Management of human resources	4
23	Technological infrastrucure	4
24	Safety	3
25	Effective crisis management	3
26	Government support	3
27	Training programmes	3
28	Digital competences	3
29	Improved customer satisfaction	3
30	Pressure from customers	3
31	Improved research and development	3
32	Drive intelligent manufacturing	2
33	Improved industry performance	2
34	Virtualisation of supply chain	2
35	Lean practices	2
36	Fewer raw materials	2
37	Sustainable production	2
38	Increased dynamic business	2
39	Cybersecurity maturity	2
40	Better business reputation	2
41	Hybrid manufacturing model	1
42	On-demand manufacturing	1
43	Rapid protyping	1
44	Remote work	1
45	Optimise risk	1
46	Knowledge management	1
47	Industrial sector	1
48	Institutional pressures	1
49	Technology adoption programmees	1
50	Digital maturity	1
51	Openness to change	1
52	Smart factory culture	1
53	Product complexity	1

	Code (Hindrance)	Code Count
1	Lack of 14.0 technologies champion	9
2	Difficuties in integrating new processes	8
3	Difficulties in creating business case	6
4	Funding	6
5	Workforce resistance to change	5
6	Difficulties in long-term planning of	5
7	Financial constraints	5
8	Lack of skills by manufacturing sector	4
9	Lack of standardisation	4
10	Uncertainty of technological needs	4
11	Lack of implementation plan	4
12	Challenge to train seasoned managers	3
13	Job automation constraints within	3
14	Difficulties in data integration	3
15	Lack of common smart factory values	3
16	Lack of corporate governance	3
17	Lack of management support	3
18	Lack of government support	3
19	Data security constraints	2
20	Lack of trust with system vendors	2
21	Lack of business model raodmap	2
22	Lack of contextualised advanced	2
23	Lack of empirical evidence	2
24	Cost of IT infrastructure	2
25	Lack of big data analysis competencies	2
26	Skills development issues	1
27	Lack of information	1
28	Threat to establish competencies	1
29	Lack of legislation	1
30	Limitation of automations	1
31	Limited automation	1
32	Lack of awareness of data security	1
33	Unfavourable culture values	1
34	Reticence from executives	1
35	Sunk costs of system adaptation	1

3.6. Technology adoption drivers and context

In this section I synthesise the technology adoption drivers and how they relate to context. The review examines the drivers and hindrances of adopting new manufacturing technological innovations within the industry 4.0 concept in relation to different contexts. Previous reviews lack an overall view of drivers and hindrances of industry 4.0 technologies adoption by manufacturing industries in developing and developed economy context. Table 10 presents the overall results of drivers in relation to context. Seven drivers relative to context are discussed in 12 articles in the sample. These seven technology adoption drivers are government support, management support, competition, customer demands, innovation, improved research and development, and digitalisation maturity. From these seven drivers, six drivers relate to a developing economy, and these are government support, management support, competition, customer demands, innovation, and improved research and development. Drivers that related to developed economies are government support, competition, customer demands, and digitalisation maturity. The results show that factors that drive technology adoption in both developing and developed economies are government support, innovation, competition, and customer demands. These driving factors that are common in both contexts are presented in fig 8 in the intersection area. Fig 9 provides a diagrammatic presentation of drivers and hindrances of technology adoption in a developing and developed economy.

Government support and context

Focusing on drivers, government support drives technology adoption in developing and developed economies (Hughes et al., 2022). However, in developing economies like India and Brazil, the required financial support required from the government by manufacturers for the technology and infrastructure is significantly higher compared to developed economies (Hughes et al., 2022). Past studies show that developed economies like Germany have made notable progress in adopting 14.0 compared to the developing economies because of government initiatives that drive adoptions (Luthra et al., 2020). Whereas 14.0 adoption is still at initial stages in developing economies like India (Luthra et al., 2020). Developing economies governments can potentially drive technology adoption by developing policies and regulations that overcome hindrances and enable adoption (Vafadarnikjoo et al., 2021).

Management support and context

Management support is expected to drive technology adoption in a developing economy by developing competent personnel for digital transformation, and development of organisational structures that permit adaptation to dynamic technological environments (Bag, Pretorius, et al., 2021; Ghobakhloo, 2020; Luthra et al., 2020; Srivastava et al., 2022). Evidence shows that management support is required in developing economies as it mostly exists in developed economies that have made significant technology adoption progress.

Competition and context

Faced with increased competition, both developed and developing economies, realise the need to continuously innovate for competitiveness (Hughes et al., 2022). Closely linked to innovation is competition. Manufacturing industries are competing on a global platform which intensifies competition. Because of competition some manufacturing are coerced to adopt new technology to survive or efficiently compete (Hughes et al., 2022).

Customer demands and context

Pressure to satisfy or meet customer demands has resulted in technology adoption by manufacturing industries, both in developing or developed economies (Hughes et al., 2022). To retain customers and attract new customers is crucial in both contexts for growth, hence the need to ensure their demands are met (Liao et al., 2017). By so doing, manufacturing companies are pressured to adopt relevant technologies to achieve set goals.

Improved research and development, and context

Improves research and development is expected to drive technology adoption in developing economies where it is scarce (Felsberger et al., 2022; Kinkel et al., 2022). Previous studies have highlighted complexities of 14.0 technologies transitions which can be mitigated by enhanced research and development, to provide the necessary information for decision-making and implementation (Hughes et al., 2022).

Digitalisation maturity and context

Digitalisation maturity drives technology adoption in a developed economy where suited infrastructure, technological competences, integration capabilities and cybersecurity maturity are generally present (Luthra et al., 2020). These enlisted enabling capabilities are generally scarce in developing economies, which explains sow-pace or no adoption (Luthra et al., 2020).

Innovation and context

Innovation is one of the factors that drive technology adoption in both developing and developed economies. To efficiently compete on the global platform, manufacturing industries need to be highly innovative (Hughes et al., 2022). For example, Chinese manufacturing industries, in a developing economy, are transitioning towards 14.0 technologies to enable innovation (Hughes et al., 2022).

The discussed drivers of technology adoption clearly show that factors that drive technology adoption in a developing economy differ from the ones in a developed economy. It is important to understand this difference to help develop frameworks are context specific to ensure that technology adoption happens at the right pace.

3.7. Technology adoption hindrances and context

Focusing on hindrances, six hindrances of technology adoption have been discussed in the context of developing and developed economies. Table 10 shows that these six hindrances are funding, personnel related issues, regulations and policy hindrances, resistance to change, technological issue, and organisational constraints. Fig 8 shows that technological issues and organisational constraints are hindrances that are evident in both developing and developed economies. While funding, personnel related issues, regulations and policy hindrances, resistance to change are hindrances that are evident in developing economies. Technological issues and organisational constraints are the only factors that related to the developed economy context.

Funding and context

The main hindrance of technology adoption in developing economies is high-cost capital (Tortorella et al., 2019; Tortorella & Fettermann, 2018). The adoption of 14.0 technologies requires intense capital, of which most manufacturing companies in developing economies cannot afford (Tortorella & Fettermann, 2018), which results in reduced adoptions of these highly sophisticated technologies by manufacturing industries despite their exceptional benefits. Developed economies on the other hand, do not face the high-cost capital challenge and have made significant progress in technology adoption.

Personnel-related issues and context

Personnel relates issues include, lack of expertise, lack of seasoned managers, lack of enhanced skills (Hughes et al., 2022; Mittal et al., 2020; Tortorella & Fettermann, 2018).

Developing economies face these personnel related issues which hinder technology adoption. While, developed economies do face these issues.

Regulations and policies and context

Regulations and policies hindrances summarise the lack of legislation and lack of favourable regulations and policies. It is important to develop regulations and policies that guide manufacturers to adopt technology at the right pace (Luthra et al., 2020). Developing economies manufacturing industries that receive less or no support from the government, are hindered from adopting technologies. Developed economies intentionally put in place initiative and government programmes that are meant to successfully drive technology adoption.

Resistance to change and context

Technology adoption is likely to negatively impact employees and other stakeholders (Hughes et al., 2022). For this reason, new technology adoption may be resisted by some or all the stakeholders (Hughes et al., 2022). The fear of job losses and changes in the supply chain may hinder adoption (Hughes et al., 2022; Lu & Weng, 2018; Luthra et al., 2020; Tortorella & Fettermann, 2018; Vafadarnikjoo et al., 2021). It becomes critical for organisations to plane for the transition to ensure that all stakeholders are ready to adopt technology.

Technological issues and context

Technological issues are prevalent in both developing and developed economies. However, developed economies do not face some of the issues that are faced in developing economies. Technological issues include integration challenges, automation challenges and automation limitation (Ghobakhloo, 2020; Govindan, 2022; Hughes et al., 2022). Developing economies may have integration issues due to lack of adequate technological infrastructure, whereas developed economies may not face these issues (Lu & Weng, 2018). Automation is associated with enhanced efficiency; however, it may lead to manufacturing disruptions that can affect both developing and developed economies which may hinder technology adoption in both contexts (Hughes et al., 2022). Automation involves utilisation of robotics and other automation technologies (Stornelli et al., 2021). While automation limitation entails the absence of appropriate infrastructure for automation integration (Hughes et al., 2022). This hindrance is synonymous with developing economies that lack apt infrastructure that can support the 14.0 technologies integration. Developed economies on the other hand do not face this challenge.

Organisational constraints and context

Organisational constraints are experienced in both contexts in different magnitudes. Organisational constrains are associated with lack of technologies champion, new processes integration difficulties, and business case development difficulties (Buer et al., 2021; Ghobakhloo, 2020; Kamble et al., 2020). Lack of 14.0 technologies champion speaks to the absence of a relationship between technological investments and productivity economic benefits (Buer et al., 2021; Govindan, 2022; Kamble et al., 2020). Lack of informed analysis of technology adoption investment and the associated benefits has emerged as the major challenge hindering technology adoption. Organisations need to develop technologies champion and efficiently compete. Technologies champion is closely linked to difficulties in integrating new processes. This challenge is experienced more in developing economies where personnel-related issues are experienced the most (Vafadarnikjoo et al., 2021). It is important for an organisation to establish the importance and relevance of technology prior adoption (Toufaily et al., 2021). However, inability to justify and motivate for technology adoption hinders adoption (Buer et al., 2021; Ghobakhloo, 2020; Stornelli et al., 2021; Toufaily et al., 2021). Developed economies together with developing economies may potentially fail to justify ad motivate for technology adoption which may hinder adoption (Lu & Weng, 2018). These two discussed challenges are constraints that need to be addressed at organisational level to enable technology enable.

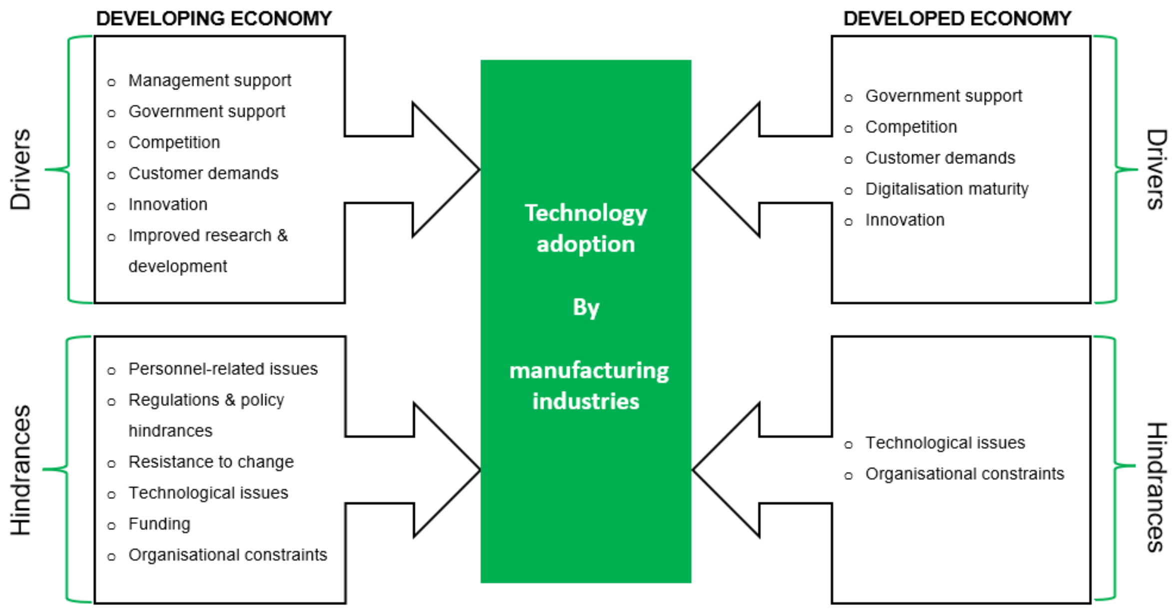

Fig 9: Drivers, Hindrances and Context

Table 10: Drivers and hindrances relative to context

	Context	Themes	Sub-categories	Authors
Drivers	***Developing***	Innovation	Innovation initiatives	Bag et al 2021; Mithas et al 2022
		Competition	Competition Industrial sector Institutional pressures Coercive pressure	Bag et al 2021; Kable et al 2020; Luthra et al 2022; Yang et al 2021 Kinnkel et al 2022
		Government support	Government support Technology adoption programmees Training programmes	Kinnkel et al 2022; Luthra et al 2022 Liao et al 2017; Srivastava et al 2022
		Management support	Management of human resources policies Senior management support	Felsberger et al 2022; Stornelli et al 2021
		Customer demands	Improved customer satisfaction Pressure from customers Product complexity	Bag et al 2021; Kinkel et al 2022; Ghobakhloo et al 2022
		Improved research and development	Improved research and development	Ghobakhloo et al 2022
	Developed	Innovation	Innovation initiatives	Bag et al 2021; Mithas et al 2022
		Competition	Competition Industrial sector Institutional pressures Coercive pressure	Bag et al 2021; Kable et al 2020; Luthra et al 2022; Yang et al 2021 Kinnkel et al 2022
		Government support	Government support Technology adoption programmees Training programmes	Kinnkel et al 2022; Luthra et al 2022 Liao et al 2017; Srivastava et al 2022
		Customer demands	Improved customer satisfaction Pressure from customers Product complexity	Bag et al 2021; Kinkel et al 2022; Ghobakhloo et al 2022
		Digitalisation maturity	Digital competences Digital maturity Integration capabilities Openness to change Smart factory culture Technological infrastrucure	Azadi et al 2021; Bittencourt et al 2021; Ghobakhloo et al 2022 Luthra et al 2022; Srivastava et al 2022; Yang et al 2021
Hindrances	***Developing***	Personnel-related issues	Job automation constraints within Lack of big data analysis competencies Lack of skills by manufacturing sector Skills development issues	Kusiak 2018; Ghobakhloo et al 2022; Laubengaier et al 2022; Srivastava et al 2022
		Regulations and policy hindrances	Lack of government support Lack of information Lack of legislation Lack of standardisation	Huber et al 2022; Govindan 2022; Liang et al 2021 Vafadarnikjoo et al 2021
		Resistance to change	Workforce resistance to change	Cui et al 2021; Govindan 2022
		Technological issues	Difficulties in data integration Limitation of automations Limited automation Data security constraints Lack of awareness of data security Lack of trust with system vendors Uncertainty of technological needs Threat to intellectual property	Ghobakhloo et al 2022; Hughes et al 2022; Kinkel et al 2017 Mithas et al 2022; Govindan 2022 Felsberger et al 2022; Huber et al 2022; Liang et al 2021
		Funding	Cost of IT infrastructure Financial constraints High costs Sunk costs of system adaptation	Ben-Daya et 2019; Huber et al 2022; Margherita & Bracinni 2020 Mithas et al 2022; Stornelli et al 2022
		Organisational constraints	Difficulties in creating business case Difficuties in integrating new processes Lack of 14.0 technologies champion Unfavourable culture values Lack of common smart factory values Lack of implementation plan Lack of business model raodmap Lack of corporate governance Lack of management support Difficulties in long-term planning of Lack of contextualised advanced technologies criteria Reticence from executives	Buer et al 2021; Liang et al 2021; Kurpjuweit et al 2021; Xu et al 2018; Laubengaier et al 2022; Dasgupta & Gupta 2019 Dohale et al 2022 Touaily et al 2021 Mithas et al 2022; Stornelli et al 2022 Felsberger et al 2022; Chen et al 2022; Bittencourt et al 2021 Kusiak 2018;

Continued Table 10: Drivers and hindrances relative to context

	Context	Themes	Sub-categories	Authors
Hindrances	***Developed***	Technological issues	Difficulties in data integration Limitation of automations Limited automation Data security constraints Lack of awareness of data security Lack of trust with system vendors Uncertainty of technological needs Threat to intellectual property	Ghobakhloo et al 2022; Hughes et al 2022; Kinkel et al 2017 Mithas et al 2022; Govindan 2022 Felsberger et al 2022; Huber et al 2022; Liang et al 2021
		Organisational constraints	Difficulties in creating business case Difficuties in integrating new processes Lack of 14.0 technologies champion Unfavourable culture values Lack of common smart factory values Lack of implementation plan Lack of business model raodmap Lack of corporate governance Lack of management support Difficulties in long-term planning of Lack of contextualised advanced technologies criteria Reticence from executives	Buer et al 2021; Liang et al 2021; Kurpjuweit et al 2021; Xu et al 2018; Laubengaier et al 2022; Dasgupta & Gupta 2019 Dohale et al 2022 Touaily et al 2021 Mithas et al 2022; Stornelli et al 2022 Felsberger et al 2022; Chen et al 2022; Bittencourt et al 2021 Kusiak 2018;

3.8. Conclusion

After presenting the review results, a detailed discussion of the results and how they address the research questions is adequately provided in chapter 4. Drivers and hindrances of technology adoption were identified relative to context, which resulted in the development of a model (see fig 8). Evidence revealed that factors that drive or hinder technology adoption in a developing economy differ from a developed economy. It is important to understand these factors to enable development of frameworks that are context specific.

Chapter 4: Discussion of literature review

4.1. Introduction

The review results presented in chapter 3 are discussed in this session. A discussion of how the structure in chapter 3 addressed the research question is also provided.

4.2. Discussion of Literature review results summary

This review examines the drivers and hindrances of technology adoption by manufacturing industries within the industry 4.0 concept relative to context. My SLR provides answers to the research questions formulated to guide this study:

RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?

RQ2 How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?

The review covers 71 articles on technology adoption by manufacturing industries of the 14.0 technologies. Table 1 lists these technologies which are CPS, IoT, big nata analytics, automation and industrial robotics, simulation and modelling, cloud technology, blockchain, augmented and virtual reality (virtualisation technology), AI, and AM. The contexts analysed are developing and developed economy.

Chapter 3 (literature review) is structured in a way that addresses RQ1 first and then RQ2. Firstly, in section 3.1, I provide a descriptive analysis of the sample articles. Secondly, in section 3.2, I provide the review objective summary. In section 3.3 I present the identified drivers of technology adoption, which answers part of RQ1. In section 3.4, technology adoption hindrances are presented and discussed, answering the other part of RQ1. Section 3.5 and 3.6 presents drivers and hindrances by context, which answers RQ2. A discussion of the literature review results and how they answer the two research questions guiding this review is presented in this chapter. The theoretical and practical implications discussion then follows. Finally, limitations of the study are discussed.

4.2.1. Discussion on descriptive analysis

The descriptive analysis illustrates the year of number of articles by year of publication, methodology assessment, and journals assessment. It is important to select a sample that is relevant to answer the research question. Fig 6 illustrates the number of articles by year of publication. Table 4 provides a methodology assessment. Table 5 presents a journal assessment of number of articles and respective percentage. From fig 6, it shows that the author engaged most with current debates on technology adoption for this review because 19 articles (26.76%) which show the highest representation of the sample were published in 2022. This is followed by 18 articles (25.35%) which were published in 2021. Considering the evolving nature of technology, it is crucial to engage with current debates to ensure the relevance of the study. Another point to note is that the number of studies published on the adoption of 14.0 technologies in the context of manufacturing has gradually risen over the past three years (70%) of the articles). The logical explanation to this recent gradual rise in these publications is the need to build resilience by organisations for uncertainties like COVID-19 crisis, which can be addressed by these new technological advancements (Dadoukis et al., 2021).

4.2.2. Discussion on drivers to technology adoption

In section 3.4, I present the identified drivers of technology adoption. Table 7 provides a listing of the technology adoption drivers, sub-categories, and the respective authors. Following the analysis, 10 drivers of technology adoption were identified, and these are corporate social responsibility, digital strategy, innovation, competition, government support, management support, digitalisation maturity, customer demands, improved research and development, and good corporate Image. From these 10 drivers, six drivers are perceived the main drivers of technology adoption by manufacturing industries because of the highest frequency code counts (see table 10) of the sub-categories linked them. These six drivers are corporate and social responsibility, digital strategy, innovation, digitalisation maturity, competition, and customer demands. The evidence presented on the identified technology adoption drivers answers the first part of research question 1: *RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?* A detailed discussion on each of the 10 drivers is presented in section 3.4. Considering that no agreement has been reached on what drives technology adoption, it is necessary to conduct more future research on this topic until it is conclusive.

4.2.3. Discussion on hindrances to technology adoption

In section 3.5, technology adoption hindrances are presented and summarised in table 9. The identified seven hindrances of technology adoption are organisational constraints, personnel-related issues, regulations and policy hindrances, resistance to change, technological issues, lack of empirical evidence, and high cost of capital. Following the content analysis notion that high frequency count insinuates the importance of the code, which subsequently mean the importance of the theme that it is linked to (Stemler, 2000), organisational constraints emerge as the main hindrance. Evidence from the sample shows that organisational constraints has been discussed the most by sample studies and needs to be overcome. The identified hindrances answer the second part of research question 1: *RQ1 What are the drivers and hindrances of technology adoption by manufacturing industries?* A detailed discussion on each of the 7 hindrances is presented in section 3.5.

4.2.4. Discussion on technology adoption drivers and context

Section 3.6 presents the seven drivers of technology adoption in developing and developed economies. Seven drivers relative to context are discussed in 12 articles in the sample. These seven technology adoption drivers are government support, management support, competition, customer demands, innovation, improved research and development, and digitalisation maturity. From these seven drivers, six drivers relate to a developing economy, and these are government support, management support, competition, customer demands, innovation, and improved research and development. Drivers that relate to developed economies are government support, competition, customer demands, and digitalisation maturity. The results show that factors that drive technology adoption in both developing and developed economies are government support, innovation, competition, and customer demands. These driving factors that are common in both contexts are presented in fig 8 in the intersection area. These identified drivers relative to context answer the first part of research question 2: *RQ2 How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?*

4.2.5. Discussion on technology adoption hindrances and context

Section 3.7 provides hindrances that relate to both developing and developed economy. These six hindrances are funding, personnel related issues, regulations and policy hindrances, resistance to change, technological issue, and organisational constraints. Fig 8 shows that technological issues and organisational constraints are hindrances that are evident in both developing and developed economies. While high-cost capital, personnel related issues, regulations and policy hindrances, resistance to change are hindrances that are evident in developing economies. Technological issues and organisational constraints are the only factors that related to the developed economy context. These identified hindrances answer the second part of research question 2: *RQ2*

How do the drivers and hindrances of technology adoption by manufacturing industries relate to different contexts?

4.3. Theoretical implications

This review provides three contributions to technology adoption by manufacturing industries and the literature on I4.0 technologies. Firstly, the study contributes to the discussion on the drivers and hindrances of technology adoption (Moeuf et al., 2020; Rad et al., 2022; Stornelli et al., 2021).

Secondly this study maps technology adoption drivers and hindrances of I4.0 technologies to developing and developed economies contexts. Although SLRs have been conducted on technology adoption drivers and hindrances (Luthra et al., 2020; Stornelli et al., 2021; Yang et al., 2021), they do not provide an overall view of drivers and hindrances of adopting I4.0 technologies relative to context. Rather, the existing SLRs have focused on drivers in a developing economy from a sustainability perspective (Luthra et al., 2020), drivers, process, and impact of technology adoption (Yang et al., 2021), barriers, enablers, and innovation types (Stornelli et al., 2021), benefits, challenges, and critical success factors of I4.0 technologies (Rad et al., 2022). By providing an overall view of drivers and hindrances of technology adoption of I4.0 technologies for developing and developed contexts, this study helps to understand the different technology adoption hindrances experienced in different contexts. This helps researchers to approach development of relevant frameworks to overcome hindrances and drive technology adoption from a context perspective. Added to that, it could help scholars and practitioners understand why technology adoption is slow in developing economies compared to developed economies where it is fast (Felsberger et al., 2022).This makes a significant contribution to the manufacturing industries that are pressured to adoption I4.0 technologies for competitiveness.

Thirdly, I developed a framework that contributes to the adoption of I4.0 technologies by manufacturing industries which provides a foundation to further discuss drivers and hindrances in the fourth industrial revolution in the developing and developed economies contexts. The framework integrates drivers, hindrances, and context, which provides guidance to the technology adoption initiatives by manufacturing industries in both contexts.

4.4. Practical implications

My review will aid managers in the manufacturing industries, digital leaders, and related practitioners who drive technology adoption of 14.0 technologies in different contexts, to be guided on how to approach technology adoption. Of importance is the understanding of factors that what drives technology adoption in a developed economy may not apply in a developing economy. Also, what hinders technology adoption in a developing economy may not hinder it in a developed economy. However, some of the drivers and hindrances are common for both developing and developed economies, and it is important to know them. Evidence shows that digital transformation informed by the adoption of 14.0 technologies is inevitable, such that more studies are required to develop technology adoption frameworks that are context specific to enable adoptions at the right pace for both developing and developed contexts.

4.5. Limitations

Added to the implications, there are limitations that are associated with conducting a systematic literature review. Firstly, the search for the sample articles was driven by selected keyword. These keywords may not be exhaustive enough to identify all the articles that are relevant for the review (Cooper, 2009). Therefore, there is no guarantee that the sample adequately addresses the formulated research question. To mitigate this shortcoming, a rigorous articles selection process was followed to ensure that good quality articles from journals rated three and above, and current literature (2017 – 2022) formed the sample for the review.

Another important limitation for this systematic literature review lies in the fact that it was be conducted by one person. Generally, multiple coders of data are engaged when conducting a systematic literature review to ensure interrater reliability of the study (Lombard et al., 2002). The sample size of 71 peer reviewed journal articles for the study is slightly lower compared to other systematic literature reviews and may potentially lessen the credibility of the study. A similar review can be conducted by more than one person, using a bigger sample size from multiple databases to ensure more credibility and reliability. Moreover, the author was conducting a systematic literature review and it is possible that research skills have not yet been gained well enough to conduct a review of this magnitude.

4.6. Conclusion

This chapter discussed literature review results in detail to demonstrate fully how the research questions were addressed. The discussion show that the research questions were addressed. From the discussions, a future research agenda is presented in chapter 5. The future research agenda discussion involves formulating research questions recommended for future research in line with the identified gaps.

CHAPTER 5: CONCLUSION

5.1. Introduction

This review examines the drivers and hindrances of adopting new manufacturing technological innovations within the industry 4.0 concept in relation to different contexts. Previous reviews lack an overall view of drivers and hindrances of industry 4.0 technologies adoption by manufacturing industries in developing and developed economy context. This study shows that there is an increase in the number of studies focusing on drivers and hindrances of 14.0 technologies adoption, in a bid to drive adoption where it is not happening and accelerate adoption pace, where it is slow (Alfaro-Serrano et al., 2021; Hughes et al., 2022; Luthra et al., 2020) . Another point to note is that the number of studies published on the adoption of 14.0 technologies in the context of manufacturing has gradually risen over the past three years (70% of the sample). The logical explanation to this recent gradual rise in these publications is the need to build resilience by organisations for uncertainties like COVID-19 crisis, which can be built by adopting 14.0 technologies (Dadoukis et al., 2021). Evidence shows that digital transformation informed by the adoption of 14.0 technologies is inevitable, such that more studies are required to develop technology adoption frameworks that are context specific to enable adoptions at the right pace for both developing and developed contexts (Rad et al., 2022).

5.2. Future research agenda

While trying to understand factors that drive and hinder technology adoption in different contexts of the manufacturing industries, I noted that different contexts have adopted different types of 14.0 technologies for various reasons. For example, European SMEs have significantly adopted IoT sensors and laser scanners to efficiently plan for production (Mittal et al., 2020). From the 14.0 technologies basket, some SMEs have strategically selected technologies that are relevant for their operation, a move that other manufacturing companies might want to consider. There is however a dearth of studies that provide technology adoption framework specific to SMEs to guide the adoption process (Mittal et al., 2020). This has resulted in manufacturing industries missing opportunities to realise increased productivity, efficiency, and revenue. However, for this review, the developing and developed economy contexts are the ones analysed. A further analysis of SMEs and large companies within a developed and developing economy is recommended for future research.

I derived future research agenda from the analysis. Table 11 lists the future research agenda that can assists scholars in technology adoption, manufacturing, and industry 4.0 domains to conduct relevant and valuable future research. In summary further work is needed to develop frameworks that motivate and guide adoption of the 14.0 technologies at an accelerated pace for competitiveness (Alfaro-Serrano et al., 2021). Lack of conclusive studies on the effectiveness of the 14.0 technologies 14.0 has resulted in few adoptions by manufacturing companies (Bhat et al., 2021; Duman & Akdemir, 2021). The absence of relevant frameworks that guide practitioners to adopt 14.0 technologies has contributed to the slow pace or no adoption (Alfaro-Serrano et al., 2021). Without adequate information pertaining to 14.0 technologies, this may cost the organisation or industry in terms of growth, revenue generation, and productivity, because these organisations may not be adopting relevant technologies to improve their competitiveness. A combination of the discussed problems show there is a problem that needs to be addressed. I, therefore, propose to highlight and suggest factors that may motivate managers to adopt 14.0 technologies at an accelerate pace for competitiveness. To overcome the identified gaps, I recommend a future research agenda that is guided by the following research questions:

1. How does new technology adoption leverage the competitiveness of medium-medium-sized manufacturing companies?
2. What are the key drivers for new technology adoption by medium-sized manufacturing companies?
3. What challenges hinder new technology adoption by medium-sized manufacturing companies?
4. What interventions can be suggested to address hinderances in new technology adoption by medium-sized manufacturing companies?

The recommended future research question will make theoretical and practical contribution to the academic field. The first theoretical contribution of recommended future study will be advancing the technology adoption literature by developing of a new technology adoption framework that motivates and guides manufacturing companies' management to adopt new technologies at an accelerated pace in a developing economy to efficiently compete. Secondly, the developed rich account of the technology adoption phenomena by combining data collected from past studies and semi-structured interviews to describe and provide a better understanding of the problem at hand, will enable the expansion of knowledge and ideas that have already been put out in the information systems discipline. Currently, some manufacturing companies do adopt new technology in their operations, but with the proposed framework, the adoption of new technology will improve through accelerated adoption pace.

Practically, the findings and recommendations that will be suggested in the recommended future research will be important to management of different manufacturing companies in a developing economy, and as such will be adopted to accelerate the pace of new technology adoption. In addition, the discussions presented in the study will shed some insights regarding adoption of new technologies aligned to organisational objectives. The development of a technology adoption model for the 14.0 technologies by a developing economy will help managers come up with technology adoption strategies and processes for competitiveness. The developed model will be tested and implemented and then guide practitioners in terms of how to go about adopting new technologies, thereby making a practical contribution.

5.3. Conclusion

A lack of agreement on what drives and hinders technology adoption relative o context has forced manufacturing companies to adopt technologies that are misaligned to strategies. I examined drivers and hindrances of technology adoption relative to context. A systematic literature review, followed by an inductive content analysis revealed that corporate social responsibility, digital strategy, innovation, digitalisation maturity, competition, and customer demands are the six main drivers of technology adoption. Secondly, the study revealed that organisational constraints, funding, personnel-related issues, regulations and policy hindrances, technological issue, resistance to change, and lack of empirical evidence are the seven main hindrances of technology adoption. Moreover, findings reveal that drivers and hindrances of technology adoption by manufacturing industries in a developing economy differ from a developed economy. The findings are integrated into a framework of technology adoption by manufacturing industries relative to context and derive recommendations for future research.

Table 11: Future research agenda

Author	Future research opportunities
Agrawal et al. (2022)	Develop strategic plans for using IoT-based tools for reducing energy consumption and improving material's recovery/reuse in the recycling of wastes within CEs. The adoption of information technologies needs to be enhanced in manufacturing sectors to reduce fossil carbon emissions.
Dohale et al. (2022)	Developing scenario planning for manufacturing strategy implementation in both developing and developed countries to improve their capabilities for implementing industry 4.0 technologies.
Ghobakhloo (2020)	Industry-specific studies on the determinants of adoption of modern Information and Digital Technology (IDT).
Kinkel et al. (2022)	Bridge between research on technology adoption processes and research on global location decisions which can explain future (technologically induced) designs of global value chains in different areas.
Kurpjuweit et al. (2021)	Explore the effects of blockchain adoption in logistics and supply chain management conducting longitudinal studies, challenging our propositions.
Laubengaier et al. (2022)	Examine when and under which conditions firms should attempt a sequential or a simultaneous adoption of Technological Process Innovation and Administrative Process Innovation.
Luthra et al. (2020)	Interdependence of the drivers may be tested through Structural Equation Modelling (SEM). Multi-areas study can determine the role of drivers in the implementation of I4.0.
Mittal et al (2020)	In future, the SMEs cases from developed and developing countries should be compared to study the effect of socio-cultural and political issues during SM paradigm adoption in SMEs.
Moeuf et al. (2020)	Explore beyond Industry 4.0 technologies and include operational opportunities such as improvement projects, tactical opportunities, and strategic opportunities that are aimed at new market prospects.
Moeuf et al. (2018)	Demonstrate whether or not Industry 4.0 initiatives could bring benefits other than flexibility.
Neumann et al. (2021)	Promote research to open up new vistas and explore I4.0 from different perspectives.
Núñez-Merino et al. (2020)	Analyze how Lean Supply Chain Management principles and practices can facilitate the adoption of Information and Digital Technologies of I4.0.
Osterrieder et al. (2020)	Describe the complete causal chain of smart factory in detail and evaluating the business or monetary impact of the implementation of Industry 4.0 technologies.
Parente et al. (2020)	Insight on the practicality of metaheuristics and machine learning in I4.0 across different sectors.
Piccarozzi et al. (2022)	The effects of new technologies (industry 4.0) on the firm’s workforce and how their interplay affects the entire organization in a synergistic perspective.
Rad et al. (2022)	The alignment of core Industry 4.0 technologies with the existing legacy information systems.
Ralston & Blackhurst (2020)	The impact of Industry 4.0 initiatives on company profitability.
Rosin et al. (2020)	The impact of Industry 4.0 technologies adoption on industrial systems.
Srivastava et al. (2022)	Longitudinal research to determine the usability of various contextual factors and Industry 4.0 adoption.
Tortorella et al. (2019)	To understand and deepen about the benefits and challenges posed by the adoption of Industry 4.0 technologies in developing economies.
Toufaily et al. (2021)	Blockchain adoption to duly acknowledge the technology’s foundational nature.
Wamba & Queiroz (2022)	Blockchain diffusion by type of industry.
Xu et al. (2021)	The impacts of age, gender, culture, and the environment on technology adoption.
Yang et al. (2021)	How do the drivers of adopting digital technologies influence the adoption process? What are the enablers, barriers and conditions of the different pathways of digital transformation?

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Appendix 1: Code Report

Project: SLR Mini Dissertation Document 2

Report created by Chipo Dzawoma on 24/11/2022

Code Report

All (88) codes

○ Absence of digital security

1 Groups:

Data security constraints

2 Quotations:

59:12 p 15 in Mithas 2022- How will artificial intelligence and industry 4 0 emerging technologies transform

IoT can result in privacy concerns, compromise the security of data and Internet Protocol (IP) addresses, and increase the chance that hackers may exploit vulnerabilities in these devices.

84:8 p 7 in Stornelli 2021 Advanced manufacturing technology adoption and innovation A systematic literature review on barriers, enablers, and innovation

Data security constraints

○ Better business reputation

Appendix 2: Code groups

Code Group
Perceived economic benefits benefits
Percieved environmental benefies
Perceived operational benefits
Perceived management benefits
Management support
Operations technology maturity
Digitalisation maturity
Corporate social responsibility
Digital strategy
Cybersecurity maturity
Government support
Regulations and policy hindrances
Optimise risk
Technological issues
Restructuring supply chain
High cost of capital
Hindraces to investment justification
Organisational constraints
Buyer-supplier relationship difficulties
Personnel-related issue
Data security constraints
Set-up preparation difficulties
Innovation
Good Corporate Image
Competition
Customer demands
Improved research and development
Lack of business model roadmap
Lack of corporate governance
Lack of empirical evidence
Lack of management support
Resistance to change
Unfavourable culture values
Lack of legislation