Gordon Institute of Business Science
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Influence Of Dynamic Sensing Capabilities On Firm Competitiveness And Mediation Role Of Inside-In Innovation

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ABSTRACT

The aim of the study is to determine the influence dynamic sensing capabilities on Firm Competitiveness and the mediation role of Inside-In Innovation. The study is done within the context of the South African energy companies, an industry undergoing profound structural and technological shifts. Hence, the research aims to deliver actionable insights for practitioners to enable robust innovation strategies that enhance Firm Competitiveness amid rapid change in the ecosystem. Furthermore, the research anticipated to close the theoretical divide in the mechanisms underpinning dynamic capabilities. Existing archetypes of open innovation fall short of explaining dynamic capabilities - mechanisms of transforming resource advantage into competitive advantage - because they omit Inside-In Innovation. Hence, the objective is to determine mechanisms underpinning Inside-In Innovation and its integration within dynamic capabilities frameworks.

Positivism paradigm deploying deductive or quantitative research approach was deployed. Existing validated survey instruments were adopted for the study targeting a minimum of 150 responses to provide meaningful analysis closer to previous studies. Ethical considerations were adhered to, and the research rigour will be determined. The study is limited by its cross-sectional nature and reliance on self-reported data from participants.

The results have shown that direct relationship between Dynamic Sensing Capabilities (DSC) and Firm Competitiveness (FC) is not statistically significant, while direct relationship between Dynamic Sensing Capabilities (DSC) and Inside-In Innovation (III) is statistically supported. Furthermore, the direct relationship between Inside-In Innovation (III) and Firm Competitiveness (FC) is statistically supported; however, the effect sizes are small indicating that complementary elements of open innovation may be required to strengthen the relationship. Lastly, H4 analysis shows that indirect path (DSC → III → FC) was considered statistically supported, while the direct path (DSC → FC) was considered not statistically supported; therefore, this indicates full mediation. Therefore, Inside-In Innovation provides mechanism of transforming resource advantage into competitive advantage and deeper reflections and reconfiguration of internal resources and processes enabling innovation, in so doing, closing the current gap in open innovation archetypes failure to explain dynamic capabilities mechanism.

KEYWORDS

Firm Competitiveness; Dynamic capabilities; Inside-In Innovation

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 [Corporate Strategy] 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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Name & Surname Signature

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List of abbreviations and acronyms

HTMT	Heterotrait–Monotrait
cSEM	Composite-based Structural Equation Modelling
CB-SEM	Covariance-based Structural Equation Modelling
AVE	Average Variance Extracted
CR	Composite Reliability
R^2	Coefficient of determination
Q^2	Cross-validated redundancy
f^2	Effect sizes
DV	Dependent variable
IV	Independent variable

CHAPTER 1: INTRODUCTION

Inside-In Innovation is argued to be a critical strategic pathway for sustaining firm competitiveness within a continuous evolving ecosystem. Despite its potential to transform organisational resilience, prior scholarship has largely neglected its potential significance, i.e., deeper reflections and reconfiguration of internal resources and processes enabling innovation (Agazu & Kero, 2024; Mathias et al., 2024; Pundziene et al., 2022; Hoed et al., 2022). This oversight represents a pressing gap in the literature that must be addressed to ensure firms remain adaptive and future ready.

The aim of the study was to determine the influence dynamic sensing capabilities on firm competitiveness and the mediation role of Inside-In Innovation. The study was done within the context of the South African energy companies, an industry undergoing profound structural and technological shifts. Hence, the research aims to deliver actionable insights for practitioners to enable robust innovation strategies that enhance firm competitiveness amid rapid change in the ecosystem. Furthermore, the research anticipated to close the theoretical divide in the mechanisms underpinning dynamic capabilities.

This chapter provides the research background, articulates business and academic relevance of the study, objectives, and scope. The chapter concludes by providing the theoretical framework underpinning the research, as well as the research question and hypotheses that guided the study.

1.1 Background

Candi and Kahn (2025) argue that high performing firms deploy open innovation to drive competitiveness with more product producing firms relying more onto open innovation for success. According to Day (2020), firms ought to deploy both Outside-In Innovation and Inside-In Innovation as they complement each other and are interrelated. The scholar further purport that Outside-In Innovation requires stepping outside firm boundaries to source market insights, while Inside-Out starts with a firm’s inward consideration of how best to deploy existing resources and capabilities externally.

In addition, Klaß (2020) argues that open innovation through Outside-In, Inside-In, and coupled innovation has potential to assist firms to adapt in a rapidly changing landscape. Furthermore, the scholar defines coupled innovation as joint innovation with partners.

Moreover, Stoeber and Kanbach (2025) postulate that firms require sensing structures and internal readiness to internalise external knowledge.

Similarly, South African energy firms are increasingly exposed to systemic paradigm shifts driven by concurrent technological advancements, evolving regulatory frameworks, mounting environmental imperatives, shifting investor expectations, intensified competitive dynamics, and escalating demands to meet sustainability commitments (Fitschen et al., 2021).

1.2 Research Problem

Gutmann (2023) argues that large firms often struggle to achieve open innovation objectives due to challenges in internal knowledge flows. Similarly, Malisić et al. (2025) emphasise that internal innovation cannot thrive without dynamic capabilities. Innovative firms, such as those in the energy sector exemplify this by internalising external trends and integrating them into new product development and processes (Mathias et al., 2024). Younas (2024) further posits that internal innovation can accelerate the commissioning of research and development projects, which typically involve prolonged lead times. Nonetheless, Pundziene et al. (2022) caution that firms with minimal "exchange of knowledge and other valuable resources between internal units" are likely to experience impediments to open innovation (p.171). This underscores the importance of Inside-In Innovation as a mechanism within internal innovation processes and as a critical component of dynamic capabilities.

Concurrently, scholarly debates on open innovation continue to evolve, with existing literature primarily emphasising Outside-In, Inside-Out, and coupled innovation as dominant archetypes (Klaß, 2020; Day, 2020; Candi & Kahn, 2025). Conversely, Gutmann (2023) critiques traditional innovation ecosystems for their limited scope, arguing that they fail to accommodate emerging concepts such as Outside-Out and Inside-In Innovation. In support, Pundziene et al. (2022) posit that Inside-In Innovation has the potential to complement Outside-In and Inside-Out approaches, thereby enriching the open innovation paradigm.

Day (2020) conceptualises the integration mechanism of Outside-In and Inside-Out Innovation as dynamic and iterative, beginning with market scanning for opportunity identification and followed by resource mobilisation and capability refinement through learning cycles. However, current archetypes of open innovation fall short of explaining dynamic capabilities' "mechanisms of transforming resource advantage into competitive advantage" because they omit Inside-In Innovation (Wang & Ahmad, 2017: 34). Gutmann (2023) further contends that Outside-In and Inside-Out approaches fail to dismantle entrenched internal silos, whereas emerging scholarship suggests that Inside-in innovation offers a transformative alternative. By fostering permeability of innovative capabilities within organisational boundaries, Inside-In Innovation enables cross-functional integration and accelerates innovation impact (Gutmann et al., 2023; Pundziene et al., 2022; Younas, 2024).

Despite its theoretical promise, empirical research on Inside-In Innovation remains limited, particularly regarding its role in transforming resource advantage into competitive advantage. Moreover, its practical application in breaking internal silos and enhancing firm competitiveness in rapidly changing environments is underexplored. This gap underscores the need for further research to clarify the mechanisms through which Inside-In Innovation operates and its integration within dynamic capabilities frameworks.

1.3 Business significance

Naidoo (2025) contends that the energy sector is experiencing profound structural and technological disruptions, necessitating adaptive strategies. In alignment, Haartman et al. (2021) assert that firms must urgently implement strategic decisions to safeguard competitiveness amid these shifts.

Although Thomas et al. (2024) acknowledge ongoing investments in technological innovation aimed at enhancing operational efficiency and meeting sustainability targets, they argue that such efforts remain insufficiently integrated into existing operations or extended into new business models. They purport that this shortfall stems from the inherent complexities of integration despite the availability of diverse opportunities. Supporting this perspective, Duranleau and Swart (n.d.) emphasise that transformation within utility companies requires dismantling entrenched silos to enable cross-functional collaboration. Similarly, Booth and Smith (2020) maintain that organisational inertia and siloed practices significantly impede energy firms' ability to adopt critical technologies, thereby constraining their capacity to achieve competitive advantage.

Therefore, this study adopts an Inside-In Innovation perspective, emphasising dynamic sensing capabilities and firm competitiveness as core constructs, with an objective of demonstrating their practical application in dismantling internal silos and fostering organisational agility to sustain competitiveness in volatile and rapidly evolving environments.

1.4 Academic significance

Pitelis et al. (2024) identify sensing, seizing, and resource transformation as the foundational elements of dynamic capabilities, with sensing enabling insights into customer needs, competitor strategies, and technology trends (Harvey, 2025). Cavusgil and Deligonul (2025) argue that dynamic capabilities foster adaptability, innovation, and resilience. However, contemporary studies remain conceptually fragmented, creating inconsistencies that hinder both theoretical development and practical application (Shiferaw & Kero, 2024). Current global dynamics demand that firms remain agile to sustain competitiveness (Wilden et al., 2013; Correia et al., 2021), while Sahakian and Jouini (2023) stress the urgency of renewing existing resource bases to enable capability transformation. When contrasted with the conceptualization of Inside-In Innovation, defined as deep reflection and reconfiguration of internal resources and processes to enable innovation, a notable gap emerges in the literature (Zhang et al., 2023; Zadegan et al., 2025).

This gap reflects the absence of scholarly clarity on mechanisms underpinning Inside-In Innovation and its integration within dynamic capabilities frameworks (Zadegan et al., 2025). Pundziene et al. (2022) explicitly call for future research into Inside-In Innovation as a construct of dynamic capabilities, while Agazu and Kero (2024) advocate for empirical studies exploring "innovation strategy and firm competitiveness from various angles" (p.15). Responding to this academic invitation, the study adopts dynamic capabilities to examine the mediating role of Inside-In Innovation in the relationship between dynamic sensing capabilities and firm competitiveness, thereby contributing to the completeness of the dynamic capabilities' mechanism.

1.5 Theoretical grounding of the research

The research was conducted using the dynamic capabilities and open innovation theoretical lenses. Teece et al. (1997) posit that in an evolving technological environment, the firm's ability to sense opportunities, seize identified opportunities, and transform resources are critical for its competitive advantage. The scholars further argue that dynamic capabilities approach is grounded on the firm's ability to renew competencies and achieve equivalence as the business environment changes, it triggers innovation and the timely adaptation, reconfiguration, and integration of resources.

The dynamic capabilities' framework is grounded on the resource-based view which posits that sustainable competitive advantage of a firm stems from resources and capabilities that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Hence, Teece (2007) argues that the core micro-foundations of dynamic capabilities enable firms to continuously identify external opportunities and detect threats, mobilise resources and implement strategic responses for value creation, and continuously adapt to changing environments.

Concurrently, open innovation framework articulates deployment of innovation through effective integration and utilisation of both internal and external sources of knowledge and innovation (Chesbrough, 2003). Furthermore, Chesbrough and Brunswicker (2014) purport that coupled innovation is the third archetype that encapsulates both external-in and internal-out innovation.

1.6 Research purpose

The aim of the study is to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning).

The following research question and sub-questions were developed and aimed to be addressed using quantitative study methodology, targeting individuals employed in the energy sector to participate in the online survey.
The main research question for this study is: What are the mechanisms underpinning Inside-In Innovation and its integration within dynamic capabilities frameworks?

Therefore, it was hypothesised that dynamic sensing capabilities (independent variable) positively influence firm competitiveness (dependent variable), and that this relationship is mediated by Inside-In Innovation. The hypotheses of this study are:
H_1: Dynamic sensing capabilities positively influence firm competitiveness
H_2: Dynamic sensing capabilities positively influence Inside-In Innovation
H_3: Inside-In Innovation positively influences Firm Competitiveness
H_4: Inside-In Innovation mediates the relationship between Dynamic Sensing Capabilities and Firm Competitiveness

1.7 The Research contribution

1.7.1 Theoretical contribution

The study's aim is to advance the dynamic capability framework by revealing the mechanisms underpinning Inside-In Innovation and integrating these into the framework, thereby addressing a critical theoretical gap. This gap arises from Sahakian and Jouini's (2023) assertion of the urgent need to renew existing resource bases to enable capability transformation, compared with scholarly conceptualisations of Inside-In Innovation as a process of deep reflection and reconfiguration of internal resources and processes to foster innovation (Teece, 2020; Pundziene et al., 2022; Zhang et al., 2023; Zadegan et al., 2025). Additionally, the current open innovation archetypes fail to explain dynamic capabilities' "mechanisms of transforming resource advantage into competitive advantage" (Wang & Ahmad, 2017: 34).

1.7.2 Business contribution

The research aims to deliver actionable insights for practitioners that enhance innovation and mitigate against siloed practices that significantly impede energy firms' ability to adopt critical technologies, thereby constraining their capacity to achieve competitive advantage (Duranleau and Swart n.d.; Booth & Smith, 2020).

1.7.3 Contextual contribution

The study is done within the context of the South African energy companies, an industry undergoing profound structural and technological shifts (Naidoo, 2025). Hence, the research aims to test if the theoretical perspectives on the research constructs are applicable.

1.7.4 Methodological contribution

The study makes use of data driven approach and uses validated questionnaires and carefully chosen respondents for assessing their firms' dynamic capabilities and Inside-In Innovation along a Likert scale (Teece, 2020).

1.8 Research scope

The study focuses on determining the relationship amongst dynamic sensing capabilities, Inside-In Innovation and firm competitiveness constructs in the South African energy sector.

The boundaries of the research are limited to individuals in the energy sector or energy value chain within South African context. The study is limited to dynamic capabilities theoretical lens to understand mediation role of Inside-In Innovation in the relationship of dynamic sensing capabilities and firm competitiveness for the completeness of dynamic capabilities mechanism. Bayighomog Likoum et al. (2020) describe the micro-foundations of dynamic sensing capabilities as environmental scanning and opportunity selection. Additionally, micro-foundations considered for Inside-In Innovation were communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning (Pundziene et al., 2022; Machado et al., 2025; Knox and Marin-Cadavid, 2023; Ting et al., 2023).

1.9 Brief outline of the document

The structure of this document is as follows:

Chapter Two	: Reviews the theoretical foundations and relevant literature informing the study, along with the conceptual model.
Chapter Three	: Presents the research questions and hypotheses derived from the literature.
Chapter Four	: Outlines the research methodology employed.
Chapter Five	: Reports the empirical findings.
Chapter Six	: Discusses the results in relation to existing literature and highlights emerging insights.
Chapter Seven	: Offers concluding remarks, practical recommendations, and outlines the study’s limitations.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The aim of the study was to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning).

This chapter critically examines the interrelationships among the key constructs of the study by reviewing and evaluating existing scholarly literature. According to Creswell and Creswell (2023), theory serves not only to explain the relationships between constructs but also to predict these relationships and inform the development of propositions or hypotheses. Accordingly, this chapter synthesises existing scholarly literature related to the research constructs and their interrelationships, with a particular lens on the dynamic capabilities' framework. It critically examines the framework's practical limitations, especially in relation to Inside-In Innovation role in its mechanism.

The layout of the chapter is shown in Table 1 below and consist of three main sections, i.e., research constructs, research framework, key relationships, and conclusion.

Table 1: Layout for literature review

Section	Sub-section
2.2 Research constructs	2.2.1 Firm competitiveness
	2.2.2 Dynamic sensing capabilities 2.2.2.1 Environmental scanning 2.2.2.2 Opportunity selection
	2.2.3 Inside-In Innovation 2.2.3.1 Communication loop 2.2.3.2 Employee collaboration 2.2.3.3 New ideas 2.2.3.4 Knowledge and asset sharing 2.2.3.5 Innovation investments and process 2.2.3.6 Organisational learning capability
2.3 Research framework	
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	2.3.3 Inside-In Innovation and firm competitiveness
	2.3.4 Dynamic sensing capabilities, Inside-In Innovation and firm competitiveness
2.5 Conclusion	

2.2 Research constructs

2.2.1 Firm competitiveness

Seminal research by Porter (1990) conceptualized firm competitiveness as a multi-level phenomenon driven primarily by national competitive advantages. However, contemporary scholarship challenges this narrow view arguing that firm competitiveness is not solely a function of national factors but is shaped by a complex interplay of contextual variables such as firm size, age, and dynamics across country, industry, and firm levels (Falciola et al., 2020; Daugaard & Ding, 2022; Dvouletý & Blažková, 2021; Hermundsdottir & Aspelund, 2021; Huang et al., 2023; Pundziene et al., 2022).

Moreover, Boikova (2021) underscores the pivotal role of consumer demand in sustaining competitiveness, reinforcing the argument that competitiveness is an ecosystem-driven construct influenced by both vertical and horizontal external factors. Consequently, firms face persistent challenges in maintaining performance and market share amid rapidly evolving contexts (Arokodare et al., 2020).

These shifts underscore the need for robust frameworks to assess firm-level competitiveness. Chen et al. (2006) propose a multidimensional approach positing that competitiveness can be evaluated through critical indicators such as cost efficiency, product and service quality, innovation and R&D intensity, managerial capability, profitability, growth trajectory, first-mover advantages, market share, and brand equity (p. 334). Complementing this view, other scholars argue that operational metrics, such as sales performance, introduction and evaluation of new products or services, and overall sales volumes, serve as practical measures of competitiveness (Mikalef & Pateli, 2017; Pundziene et al., 2022).

Expanding beyond performance metrics, Soniewicki and Hauke-Lopes (2023) advance the concept of competitor orientation, asserting that firms that systematically analyse the strengths, weaknesses, and long-term capabilities of current and potential rivals are better positioned to shape industry ecosystems, capture emerging markets, and create new ones. This perspective reframes competitiveness as a strategically proactive construct, requiring firms not only to respond to market dynamics but to anticipate and influence them, thereby redefining competitive advantage in volatile environments.

2.2.2 Dynamic sensing capabilities

2.2.2.1 Introduction

Chatterjee et al. (2023) define dynamic capabilities as “high-level routine that, together with its implementing input flows, confers upon an organization’s management a set of decision options for producing significant outputs of a particular type” (p. 1). The dynamic nature of these capabilities is premised on adaptability to fast-paced, highly turbulent, evolving business environments, and ability to reconfigure resources. Pitelis et al. (2024) posit sensing, seizing of opportunities and transformation of resource base are critical elements of dynamic capabilities. Sensing focuses on data gathering and synthesising through environmental scanning and opportunity identification, While seizing refers to mobilising resources and closing internal gaps to ensure the exploitation of identified opportunities, transformation ensures adaptability and continuous reconfiguration of resources to maintain competitiveness (Teece, 2020).

However, Leeman et al. (2021) challenge the linear interpretation of these elements, arguing that they are neither sequential nor inherently interconnected, thereby contradicting earlier scholarship that assumes a chronological progression. In contrast, Aghimien et al. (2021) emphasise the strategic imperative for firms to embed all three elements within their operational frameworks to build resilience in an increasingly volatile business landscape. This debate underscores the evolving nature of dynamic capabilities theory and its practical implications for sustaining competitive advantage.

2.2.2.2 Dynamic sensing capabilities

Scholarly literature conceptualizes sensing capabilities as systematic environmental scanning, involving the detection and collection of data from both internal and external sources with the objective of enabling analysis and dissemination of actionable insights (Teece, 2020; Teece et al., 2020). Punziene et al. (2022) reinforce this view, asserting that “a firm’s sensing capabilities are crucial under the current business environment for it to be able to detect the vast amount of diverse knowledge and technology that exists to assess these against the firm’s business needs, and to select the ones with the most potential to fit their needs while leaving aside the not relevant ones” (p. 159). Beyond technological and knowledge scanning, sensing capabilities extend to capturing insights on customer needs, competitor strategies, and emerging technology trends, thereby enabling firms to identify opportunities and threats within dynamic landscapes and to develop tacit knowledge and experiential learning (Harvey, 2022; Zabel, 2023; Khan et al., 2020).

However, this perspective has been challenged by Arnt (2019) arguing that, at times, routine market scanning and sensing capabilities, particularly environmental scanning, are used interchangeably blurring the strategic nature of the latter. The scholar further argues that there is no aligned scholarship on theoretical constituents nor practical application of dynamic sensing capabilities. Similarly, Shiferaw and Kero (2024) underscore the lack of conceptual and practical consensus on sensing dynamics in the scholarly literature. This is evident in its lack of differentiation from competitive intelligence which involves data collection and synthesis thereof, proactively managing threats and exploiting opportunities (Bornay-Barrachina et al., 2025). The scholars further argue that dynamic sensing capabilities are curated by the leadership in an organisation and internal culture of learning.

Moreover, Foss et al. (2023) posits that the leadership of the firm plays a crucial role in enabling the three dimensions of dynamic capabilities, i.e., embedding shared vision through sensing, operationalising seizing through ecosystem specific investments, and problem solving through reconfiguration of resources. In support, Teece et al. (2020) argue that management need to be positioned to recognise the opportunity set and have data gathering and sharing systematic approach. The scholars argue that organisational design including processes and incentives should foster collaboration.

According to Bayighomog Likoum et al. (2020), insights gathered from environmental scanning should inform internal decisions on emerging opportunities and threats relating to technology and market changes. In addition, Zabel et al. (2023) purport that emerging opportunities can often be unlocked through co-creation with customers, suppliers, and competitors. However, Bayighomog Likoum et al. (2020) argue that such integration of external information and internal resources and competencies are at the core of dynamic capabilities framework. Furthermore, Heaton et al. (2023) argue that allocation and reallocation of resources triggered by changes in the opportunity space, requires flexibility and timely decisions.

This provides rationale on why some companies struggle over time to reach the same level of economic value achieved by their peer company operating in the same markets and exposed to the same environment of business (Gerhart & Feng, 2021). However, dynamic sensing capabilities differ from one firm to another due to factors such as size and business model (Zabel et al., 2023).

2.2.3 Inside-In Innovation

2.2.3.1 Introduction

Innovation is a broad concept ranging from technology to policy; however, it is critical to solving organisational challenges (Matos et al., 2022). Yang et al. (2024) suggest that innovation in companies unlocks insuperability, high-quality product development, and enhance competitiveness. The scholars further purport that a closer look at mutual influences amongst companies often unlocks new opportunities due to imitations and mimicking each other’s decisions. This entails technology spillovers where companies access innovation related information on their peers and that influences their own innovation decisions and technology advancements.

Akimov et al. (2023) posit that open innovation enables firms to leverage both internal developments and external competencies and innovations. This reinforces an existing perspective that a firm’s success is contingent upon the effective integration and utilisation of both internal and external sources of knowledge and innovation (Chesbrough, 2003). In addition, Chatterjee et al. (2023) argue that innovation relies on companies deploying resources in accordance with the resource-based view theory.

Scholars claim that open innovation can broadly be categorised into two archetypes: inbound innovation, which involves the integration of external knowledge into the organization; and outbound innovation, which entails the external dissemination of internal knowledge and capabilities (Enkel et al., 2009; Chesbrough & Brunswicker, 2014). However, Chesbrough and Brunswicker (2014) purport that coupled innovation is the third archetype that encapsulates both external-in and internal-out innovation, for example, this manifests in strategic alliances and joint ventures. Contrary, Pundziene et al. (2022) posit that Inside-In Innovation, as a third archetype of open innovation, complements external-in and internal-out innovations, while Gutmann et al. (2023) argues that Inside-In and Outside-Out Innovation archetypes require academic exploration.

2.2.3.2 Inside-In Innovation

Inside-In Innovation construct refers to deeper reflections and reconfiguration of internal resources and processes enabling innovation; while internal innovation refers to all innovation activities executed within a firm, e.g., research and development activities (Zhang et al., 2023; Zadegan et al., 2025). Another distinction that should be made from Inside-In Innovation is innovation ambidexterity which is critical in fostering internal adaptability by focusing on balancing exploitative and explorative innovation to produce improved or radical products respectively (Chang & Hughes, 2012; Saleh et al., 2023).

According to scholarly literature, Inside-In Innovation enables permeability of innovative capabilities internally within an organisation, breaking internal silos to achieve innovation impact (Gutmann et al., 2023; Pundziene et al., 2022; Younas, 2024). Conversely, Forsman (2021) argues that failures in delivering innovation objectives are due to challenges encountered during innovation processes. Pazaitis (2020) makes a similar point that empowerment participation enables strategic reconfiguration of internal resources to effectively support innovation objectives, and this is critical for the success of open innovation.

However, an argument can be made that the above scholarly contribution was implicitly referring to Inside-In Innovation evidenced by its definition and claim that it complements Inside-Out and Outside-In Innovation through ensuring dissemination of knowledge and resources within organisation boundaries (Pundziene et al., 2022). Contradictory, Hartono and Rafik (2021) attributes barriers of innovation to lack of skilled personnel, financial, and regulatory issues and these can be mitigated by external-in innovation.

The following sub-sections interrogates the micro foundations of Inside-In Innovation, i.e., communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning (Pundziene et al., 2022; Machado et al., 2025; Knox and Marin-Cadavid, 2023; Ting et al., 2023).

Machado et al. (2025) argues that collaborative and transparent work environments underpinned by effective internal communication tend to facilitate innovative workforce. Complementing this view, Hart (2025) posits that organisations with embedded formal feedback loops can “foster continuous adaptation, employee engagement, and knowledge sharing” (p. 398). However, Machado et al. (2025) caution that internal conflict and resistance in organisations hinders innovation. On the other hand, Knox and Marin-Cadavid (2023) argue that employee collaboration is pivotal for unlocking innovation within firms, necessitating the allocation of additional resources, structural adjustments, and redistribution of decision-making authority. Similarly, Van der Voet & Steijn (2021) suggests that employee collaborations can unlock innovation potential through existing expertise, connections, financial resources, and knowledge within an organisation. However, the scholars caution that this visionary leadership enables team cohesion.

Furthermore, Valtonen et al. (2023) claim that new ideas required to enable Inside-In Innovation depends on individual level factors such as expertise, social currency, and motivation levels. However, they caution that idea generation on its own is not sufficient and it needs to translate into implementation through resource allocation and sponsorships. Meanwhile, Ting et al. (2023) argue that knowledge management infrastructure and processes are indispensable for enabling Inside-In Innovation, with organisational culture and leadership serving as primary drivers. This perspective is complemented by Harsono et al. (2025) who contend that the success of such initiatives hinges on a nuanced understanding of market dynamics. Furthermore, Randhawa et al. (2016) and Fayyaz et al. (2021) emphasize that top management support, internal knowledge flows, technology transfer, and related investments are critical for stimulating open innovation effectiveness. However, Yeboah (2023) challenges the efficacy of current practices, asserting that firms often engage in fruitless knowledge-sharing sessions and arguing that these processes must be strategically aligned with business objectives and resource allocations to generate tangible value. Conversely, Stojcic et al. (2025) caution that while asset sharing may foster innovation, excessive reliance on intra-group resources, such as shared assets and employee mobility, can lead to competency traps, ultimately constraining innovation and undermining firm performance. Collectively, these insights underscore that knowledge management is not merely a structural necessity but a strategic imperative requiring alignment, adaptability, and balance to avoid systemic inefficiencies.

In addition, Smith (2025) asserts that investment in innovation produces a multiplier effect on firm competitiveness; however, this optimistic view is tempered by Zamaar et al. (2023) who caution that the absence of enabling tools and systems for innovation processes introduces significant decision-making risks. Similarly, Akimov et al. (2023) argue that the viability of open innovation models is contingent upon equipping personnel with project competencies aligned to business needs in volatile markets. Extending this discourse, Saleh et al. (2023) emphasize that managing innovation balance is shaped by a constellation of determinants, including process mechanisms, organisational learning, leadership styles, technology investments, organisational contexts, environmental uncertainties, and institutional pressures (p. 3013). Collectively, these perspectives underscore that while innovation investment is pivotal, its success depends on systemic support structures, competency development, and contextual adaptability.

While Pedraja-Rejas et al. (2025) contend that dynamic sensing capabilities underpin holistic organisational learning by integrating continuous improvement and innovation, this view is reinforced by scholars who argue that in volatile environments, organisational learning capability is not merely advantageous but a critical determinant of resilience and sustained competitiveness (Wu & Wang, 2014; Efendi et al., 2020).

2.3 Research framework

The study deployed the tenets of dynamic capabilities theory with open innovation lens explored as a supporting set of processes to understand the role of Inside-In Innovation in the relationship between dynamic sensing capabilities and firm competitiveness. Teece et al. (1997) posit that in an evolving technological environment, the firm's competitive advantage depends on its ability to leverage its internal resources. The scholars further argue that dynamic capabilities approach is grounded on the firm's ability to renew competencies and achieve equivalence as the environment of business changes, triggering innovation and timely adapting, reconfiguring, and integrating resources. The framework articulates the dynamism of both external and internal firm ecosystem as well as the ability to renew firm competencies to reposition in equivalence to the change anticipated in the operating context (Mansouri et al., 2022).

The dynamic capabilities framework is grounded on the resource-based view which posits that sustainable competitive advantage of a firm stems from resources and capabilities that are valuable, rare, inimitable, and non-substitutable, which posit that resources should provide strategic value, resources must enable firms to exploit market opportunities, be unique to the firm, difficult to replicate, and lack viable alternatives (Barney, 1991). However, the dynamic capabilities framework corrects for the static posture of the RBV by considering the dynamism of the ecosystem.

Hence Teece (2007) articulates micro-foundations of dynamic capabilities as those "skills, processes, organisational structures, decision rules, and disciplines" which are embedded in the "sensing, seizing, and reconfiguring capacities" unique to the firm (p. 1319). Scholarly literature conceptualises sensing capabilities as systematic environmental scanning whereby detection and systemically collecting data from various sources external or internally, with an objective of enabling analysis and dissemination of insights (Teece, 2020; Teece et al., 2020). Bayighomog Likoum et al. (2020) suggests that insights gathered from environmental scanning should inform internal decisions on emerging opportunities and threats relating to technology and market changes. In addition, scholars argue that such integration of external information and internal resources and competencies are at the core of dynamic capabilities framework. However, scholarly literature is muted on the mechanism that relates to deeper reflections and reconfiguration of internal resources and processes enabling innovation, i.e., Inside-In Innovation (Zadegan et al., 2025). In addition, Teece et al. (1997) postulate absence of mechanics to be deployed through dynamic capabilities to realise competitiveness. Therefore, there is insufficient research, if any, on the interplay amongst dynamic sensing capabilities, Inside-In Innovation and firm competitiveness.

Bogers et al. (2019) claim that there are limited studies deployed to understand open innovation outcomes using dynamic capabilities framework. Concurrently, open innovation framework articulates deployment of innovation through effective integration and utilisation of both internal and external sources of knowledge and innovation (Chesbrough, 2003). Furthermore, Chesbrough and Brunswicker (2014) purport that coupled innovation is the third archetype that encapsulates both Outside-In and Inside-Out Innovation. However, the current open innovation archetypes fail to explain dynamic capabilities' "mechanisms of transforming resource advantage into competitive advantage" because it omits the Inside-In Innovation (Wang & Ahmad, 2017: 34).

Recent studies that deployed the frameworks are as follows:

Table 2: Related studies on Dynamic capabilities and Open innovation frameworks

Scholar	Research objectives	Frameworks	Study limitations	Future study	Journal & Ratings
Gutmann (2023)	Extending Open Innovation: Orchestrating Knowledge Flows from Corporate Venture Capital Investments	Open Innovation theory and Dynamic Capabilities	Based on qualitative case studies, limited generalisability. Focused on large firms with established CVC units—may not apply to SMEs.- Does not quantify performance impact.	Quantitative studies linking CVC orchestration to firm performance. Explore sectoral differences and SME contexts. - Investigate long-term dynamic capability development through CVC.	R&D Management.
Teece (2020)	Hand in glove: Open Innovation and the Dynamic Capabilities Framework	Dynamic capabilities and Open Innovation frameworks	Relies largely on theoretical synthesis and one single-case study (Haier). Lacks broad empirical testing across industries or geographies.	Conduct cross-industry and multi-case empirical studies to validate theoretical linkages. Investigate metrics relating specific DC micro-foundations to Open Innovation outcomes. Examine causal mechanisms and boundary conditions across diverse organizational contexts.	Strategic Management Review.
Ferreira et al. (2020)	Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation	Dynamic capabilities	Cross-sectional design limits causal inference. Based on single key informant per firm. Sample restricted to Portuguese firms	Use longitudinal designs for causality. Collect data from multiple respondents per firm. Test in other national and industry contexts to verify generalisability	Technovation.
Pundziene et al. (2022)	Impact of knowledge/resource exchange between internal units on Open Innovation	Dynamic Capabilities	Cross-sectional design; limited generalizability beyond studied firms	Investigate Inside-In Innovation as a construct within dynamic capabilities	European Journal of Innovation Management (EJIM, B).
Cavusgil & Deligonul (2025)	Dynamic capabilities' role in adaptability, innovation, and resilience	Dynamic Capabilities	Lacks empirical evidence; primarily theoretical commentary	Address conceptual fragmentation and develop unified frameworks	Journal of International Business Studies (JIBS, A*).
Harvey (2025)	Microfoundations of sensing capabilities: From managerial cognition to team behavior	Dynamic Capabilities	Focused on managerial cognition; lacks quantitative evidence across diverse contexts	Study integration of sensing with organizational learning and innovation platforms	Strategic Organization (Sage, A).
Pitelis et al. (2024)	Core elements of dynamic capabilities	Dynamic Capabilities Framework	Conceptual emphasis; empirical validation across industries is missing	Examine how these elements interact with internal innovation mechanisms	Journal of Management Studies (JMS, A).

Therefore, the study deploys the two theoretical lenses: dynamic capabilities and open innovation as they possess organisational and managerial implications and further display unique differences (Teece, 2020). Furthermore, open innovation focuses on processes while dynamic capabilities framework is strategic in nature, focusing on management decision making and competitiveness, thus bringing forth complementary strengths to the study.

2.4 Theory and hypotheses development

2.4.1 Dynamic sensing capabilities and firm competitiveness

Umulkher and Gichinga (2024) posit that sensing capabilities exert a direct influence on firm competitiveness, a view echoed by scholars who identify a strong linkage between sensing dynamics and competitive advantage (Fainshmidt et al., 2019; Al Dhaheri et al., 2024). Supporting this position, Chowdhury and Quaddus (2021) argue that deploying dynamic capabilities is imperative for mitigating financial risk, enabling firms to achieve competitiveness in new markets regardless of contextual volatility and to capitalise on potential growth opportunities (Gnizy et al., 2014). Furthermore, Agazu and Kero (2024) conceptualize competitiveness as an iterative process requiring resilience and strategic exploitation of emerging opportunities.

Conversely, Al Dhaheri et al. (2024) contend that all constructs of dynamic capabilities, including sensing, seizing, and resource reconfiguration, are critical for firm survival, particularly in optimizing operations during crises. This perspective positions competitiveness as a holistic outcome of integrated dynamic capabilities rather than a function of sensing alone. Reinforcing this argument, Eisenhardt and Martin (2000), Zott (2003), and Al Dhaheri et al. (2024) caution against assuming a direct causal link between sensing capabilities and competitiveness, suggesting instead that sensing operates synergistically with other capability dimensions to drive sustainable advantage.

Although the researcher acknowledges the existence of opposing scholarly perspectives, a positivist paradigm has been adopted. Therefore, hypothesis posed is as follows:

H_1: Dynamic sensing capabilities positively influence firm competitiveness.

2.4.2 Dynamic sensing capabilities and Inside-In Innovation

Farzaneh et al. (2022) conceptualise ambidextrous firms as those leveraging existing capabilities to drive incremental innovation while simultaneously exploiting new opportunities through radical innovation. Building on this, Bogers et al. (2019) argue that firms must continuously formulate and execute medium- to long-term R&D strategies through the dynamic capability triad of sensing, seizing, and transforming. Sensing, characterised by systematic environmental scanning, enables the acquisition of new information and knowledge critical for identifying emerging opportunities. Moreover, Goerzig and Bauernhansl (2018) contend that these capabilities provide valuable insights into customer perceptions of value, necessitating targeted internal resource investments to develop products and services that effectively align with evolving customer needs.

However, existing scholarly work does not make a clear distinction between dynamic sensing capabilities and Inside-In Innovation except acknowledgement of the role innovation plays in uncertain times and shifting market dynamics (Chesbrough, 2003). In support of this argument, Malik (2013) argues that learning mechanisms is one of the micro foundations of sensing capability, while Li & Wang (2022) purport that organisational learning increases innovation performance. Furthermore, the scholar argue that high construal managers display more sensing capabilities in comparison to their peers and that managerial intellectual abilities are critical in enabling sensing capabilities internally, facilitated by effective communication, scale, enabling processes, and continuous organisational learning loop (Harvey, 2022; Harvey, 2025). The following sub-sections interrogates dynamic sensing capabilities in relation to the micro foundations of Inside-In Innovation.

Shani et al. (2025) argue that continuous adaptation in turbulent ecosystems necessitates feedback loops and internal communication as critical mechanisms for sensing environmental shifts. Feedback loops, defined as cyclic processes of collecting outcome data and integrating it into decision-making, enable iterative learning and responsiveness (Siswadi et al., 2023; Auqui-Caceres et al., 2023). Building on this, Stoeber and Kanbach (2025) posit that the effectiveness of sensing capabilities, particularly the active interpretation of emerging market signals and technological disruptions depends on these communication loops, which continuously refine internal capabilities and enhance organisational agility. Meanwhile, Stoeber and Kanbach (2025) postulate that sensing capabilities are intrinsically linked to open innovation practices, particularly through mechanisms such as permeable organisational boundaries and collaborative ecosystems. Reinforcing this view, Pundziene et al. (2022) argue that effective management of collaboration among employees and business units is essential for achieving open innovation outcomes.

Furthermore, Diaz et al. (2017) contend that firms with limited resources can leverage employee motivation and internal collaboration networks to sustain innovation efforts, while Steiber and Alänge (2020) advocate for the establishment of dedicated innovation units or joint teams with external partners to seize opportunities for mutual benefit. Collectively, these perspectives underscore that sensing capabilities and collaborative structures operate synergistically to enable open innovation, particularly in resource-constrained contexts. In addition, Chesbrough (2017) argues that managing the impact of internal innovation and transferring inflowing ideas and knowledge across organisational boundaries remains challenging due to siloed team structures. In contrast, Stoeber and Kanbach (2025) contend that these ideas can be effectively transformed into firm-level processes, thereby operationalising innovation and embedding it within organisational routines.

Furthermore, Chesbrough (2017) asserts that Inside-In Innovation necessitates a distributed mindset to fully leverage internal assets and knowledge. In contrast, Stoeber and Kanbach (2025) argue that knowledge is inherently fluid and co-shaped through internal and external interactions; consequently, in the absence of robust internal capabilities, external knowledge may be perceived not as an enabler but as a barrier to innovation. While Akimov et al. (2023) posit that the success of open innovation model depends on equipping the personnel with project competencies that meet business needs in uncertain, volatile market. Extending this perspective, Saleh et al. (2023) argue that some of the determinants of managing innovation balance are: “process mechanisms, organisational learning, leadership styles, technology investments, organisational contexts, environmental uncertainties, and institutional pressures” (p. 3013).

Blocker et al. (2024) argue that firms committed to continuous learning and adaptability must actively embrace market dynamics and remain attuned to emerging opportunities. Reinforcing this perspective, Bayighomog Likoum et al. (2020) suggest that organisations with strong sensing capabilities demonstrate proficiency in learning, data collection, and synthesis, thereby positioning themselves to anticipate shifts and respond strategically. Collectively, these insights underscore that open innovation effectiveness is not solely a function of external collaboration but requires robust internal capability development and systemic alignment with organisational and environmental contingencies; and further demonstrates that sensing is a strategic enabler of organisational agility.Therefore, hypothesis posed is as follows:

H_2: Dynamic sensing capabilities positively influence Inside-In Innovation

2.4.3 Inside-In Innovation and firm competitiveness

Current global dynamics demand that firms remain sufficiently agile to sustain competitiveness (Wilden et al., 2013; Correia et al., 2021). However, Sambamurthy et al. (2003) argue that the mechanism to be followed in adapting urgently in such contexts is not clear. Similarly, Sahakian and Jouini (2023) suggest that existing resource base for current operations requires renewal to enable required capability transformation and further emphasise on the urgency thereof. Contrasting these perspectives with the definition of Inside-In Innovation, i.e., deeper reflections and reconfiguration of internal resources and processes enabling innovation, a notable gap in literature emerges (Zhang et al., 2023; Zadegan et al. 2025).

However, Afum et al. (2021) argue that firms need to find creative ways to sustain their operations and remain competitive, suggesting that Inside-In Innovation is embedded in the broader innovation construct. Recent scholarship purport that innovation improves financial performance and firm competitiveness (Agazu & Kero, 2024; Sukumar et al., 2020; Obeidat et al., 2021). However, such companies ought to have processes and structures that foster innovation to be in a better position to compete with their peers (Sukumar et al., 2020).

Mallén-Broch and Domínguez-Escrig (2021) argue that some of the factors that facilitates innovation are: “experimentation, dialog, participative decision-making, risk-taking, and interaction with the external environment” (p. 309). Most of these factors are driven by management, and Sein and Dmytrenko (2023) cautions that in the absence of management strategic alignment and execution, internal innovation would be ineffective and fail to deliver on competitiveness. According to Ferreira et al. (2020), innovation outputs are characterised by shortened product process time in relation to the competitors, strong market performance of new products, and timeously substituting outdated products resulting in better firm performance (Ferreira et al., 2020). In addition, Chatterjee et al. (2023) argues that companies tend to outperform others and demonstrate superior performance when dealing with valuable, rare, inimitable, and non-substitutable resources supporting innovation. The following sub-sections interrogates micro foundations of Inside-In Innovation in relation to firm competitiveness.

Stacho et al. (2019) postulate that structured communication loop inclusive of the bottom-up communication improve internal collaboration and firm competitiveness. However, the scholars posit that informal communication has potential value, though it is often ignored in firms. Conversely, Nwabueze et al. (2018) argue that during crises, these communication loops tend to collapse despite existing processes, resulting in diminished firm competitiveness. Meanwhile, Nwabufo and Obodozie (2025) suggest that collaboration across teams enables innovation and results in firm competitiveness and resilience. However, Moordiningsih et al. (2024) argues that the firm's rewards system needs to be aligned with collaborative networks to result into firm performance.

Additionally, Cohen and Keren (2022) postulate that innovative breakthrough ideas emerge when diverse perspective come together. In support, Yang et al. (2023) suggest that company competitiveness hinges upon its innovation ability, technology orientation, and information flow. This suggests that absence of processes, resources, and structures would be detrimental to implementing innovation. Conversely, some scholars argue that network externalities and knowledge spillovers from the industry and country level offer more significance than internal innovation (Zhang et al., 2020). However, the study cannot be conclusive as it did not consider Inside-In Innovation in their scope.

Moreover, Bibi et al. (2020) posit that firm competitiveness is also driven by organisational learning and employees' inclination to innovate. Therefore, firms must ensure development of unique capabilities and ensure expansion of its resource base through embedding continuous learning in the organisation to harness its competitiveness (Helfat, 2007). Despite extensive research, little attention has been paid to Inside-In Innovation; however, interrogation of existing literature implies potential relationship between Inside-In Innovation and firm competitiveness; therefore, the hypothesis posed is:

H_3: Inside-In Innovation has a positive influence on firm competitiveness

2.4.4 Dynamic sensing capabilities, Inside-In Innovation and firm competitiveness

Barney (1991) argues that the firm's competitiveness is driven by its ability to proactively reconfigure its internal resources. However, Akhtar et al. (2020) posits that dynamic capabilities cannot be reduced to a linear mechanism as it is characterised by complexities. These complexities include inclination to identify and dimension real opportunities and threats timeously, reconfigure internal resources in such a way that intended results will be realised (Teece et al., 1997; Barreto, 2010; Mansouri et al., 2022).

Additionally, Sarwar et.al. (2023) postulate that dynamic capabilities systematically solve company's issues through timely and market related decisions, improving and developing new organisational competencies and ensuring that it is future ready and thus generating long term competitiveness. The scholars further argue that competitiveness is anchored on a strategy that is challenging to duplicate and unlocked through dynamic capabilities. Furthermore, McDougall, Wagner, and MacBryde (2022) cautions that dynamic capabilities are not a set of capabilities to be added to competitive resource, but rather a concept deliberately enabling reconfiguration of the resource base as per required.

Ferreira and Coelho (2020) contend that the duality of exploratory and exploitative innovation modes forms the foundation of Inside-In Innovation, positioning these processes as essential for organisational adaptability. While exploration facilitates the generation of novel ideas for products and services, exploitation ensures the refinement and enhancement of existing concepts, thereby creating a dynamic tension that drives continuous improvement. The authors argue that the ability to identify emerging opportunities and threats is not merely reactive but constitutes a strategic imperative that enables timely decision-making and organisational transformation. This capability serves as a precursor to innovation, applying an indirect yet significant influence on competitive advantage and overall performance.

Farzaneh et al. (2022) suggest that there is a relationship between intellectual capital and innovation ambidexterity which is enabled by dynamic capabilities; however, this research was restricted to pharmaceutical industry data from Iran. Sarwar et al. (2022) conducted a similar study in Pakistan, investigating the interactions of the corporate social responsibility, dynamic capabilities, and business competitiveness constructs, including the mediation role of green innovation and environmental performance. Limitations of these studies were location bound and limited to a specific sector, hence recommendations for future studies include extending this study to other regions and sectors.

Scholars argue that dynamic capabilities in the context of dynamic markets, characterised by altered competitive foundations, explain competitiveness more effectively (Ferreira & Coelho, 2020). According to Falahat et al. (2020), a firm's competitiveness is fundamentally rooted in its capacity to extract market intelligence, through identification of emerging opportunities and reconfiguring resources to innovate products at a price that customers are willing to pay.

Correira (2021) explains that such intelligence that emanates from customers and competitors should be internalised by the firm to enable proper respond to the trends and challenges. Harvey (2025) argues that the validity of this relies on the deployment of dynamic capabilities and paves way for a firm's competitiveness over time, while Bayighomog Likoum et al. (2020) posits that firms with inclination towards dynamic sensing tend to draw insights from gathered data and reconfigure its resources to defend their market positions or perform better in turbulent market environment. Moreover, Pundziene et al. (2022) suggest existence of indirect relationship between dynamic capabilities and competitive performance of firms which is mediated by open innovation The following sub-sections interrogates dynamic sensing capabilities, micro foundations of Inside-In Innovation and firm competitiveness.

Figueired et al. (2025) contend that reward systems serve as a strategic lever for fostering employee collaboration, thereby enhancing firm competitiveness. Nevertheless, scholars caution that unfair performance evaluations and misaligned incentives can undermine innovation, creating organisational rigidity rather than agility. Similarly, Moordiningsih et al. (2024) argue that the effectiveness of reward systems is contingent upon their alignment with collaborative networks, asserting that such congruence is essential for translating collaborative behaviours into sustained firm performance. Meanwhile, Zabel and O'Brien (2024) claim that sensing capabilities are critical to development of new ideas and ensuring firm competitiveness. Similarly, Stoeber and Kanbach (2025) also argue that sensing enables competitiveness through new ideas emanating from the external environment. In addition, Liu (2022) posits that communication, i.e., tacit or explicit, characterized by shared meaning, transferability, and specificity - underpins dynamic capabilities.

Furthermore, Bornay-Barrachina et al. (2025) contend that organisational learning influences dynamic capabilities; however, this is contingent on the type of learning and leadership. Furthermore, Ferreira et al. (2020) emphasize that organisational learning capability operates as a critical enabler, reinforcing the firm's capacity to balance exploration and exploitation effectively within Inside-In Innovation. Therefore, the proposed hypothesis is as follows:

H_4: Dynamic sensing capabilities and firm competitiveness are mediated by Inside-In Innovation.

2.4 Conceptual model

The study is grounded on the resource-based value theory and dynamic capabilities framework and aims to investigate the relationship between dynamic sensing capabilities, Inside-In Innovation and firm competitiveness. Conceptual model is proposed to depict path relationships (see Figure 1). The researcher proposed: 1) direct relationship between dynamic sensing capabilities and firm competitiveness; 2) direct relationship between dynamic sensing capabilities and Inside-In Innovation; 3) direct relationship between Inside-In Innovation and firm competitiveness; and 4) the relationship between dynamic sensing capabilities and firm competitiveness is mediated through Inside-In Innovation.

The conceptual model is included to visually depict proposed relationships and guide hypothesis development in Figure 1. This shows the relationship between each construct and the mediator.

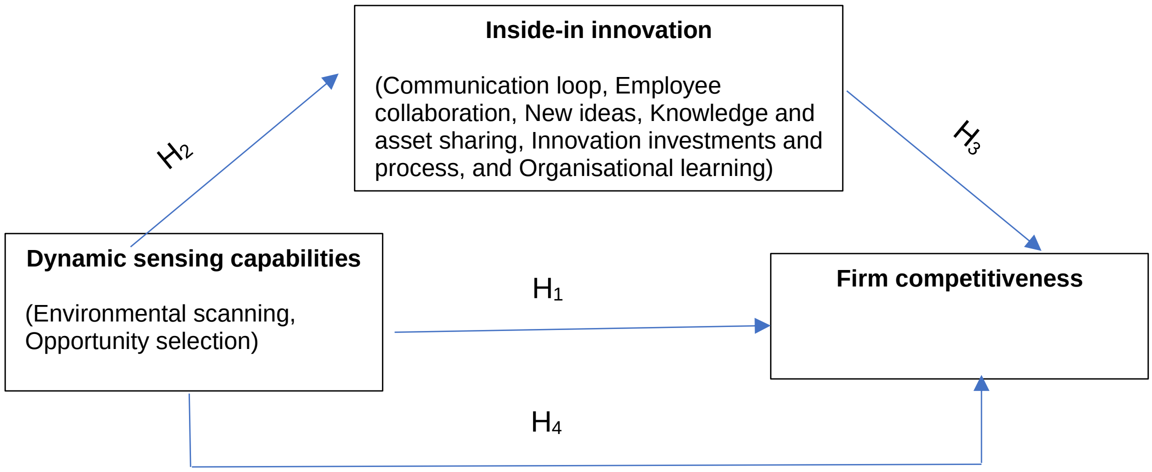

Figure 1: Proposed conceptual model

2.7 Conclusion

This chapter engaged with existing literature to interrogate theoretical perspectives on dynamic sensing capabilities, Inside-In Innovation, and firm competitiveness, emphasising the interconnections posited in prior research. The review contends that scholarly consensus largely supports the complementarity of these constructs within the dynamic capabilities and open innovation frameworks, while acknowledging nuanced debates on their strategic implications.

CHAPTER 3: RESEARCH QUESTION AND HYPOTHESES

The aim of the study was to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning).

This chapter articulates the research question of the study and presents the hypotheses developed in addressing the research question.

3.1 The research question

The main research question for this study is: “How does Inside-In Innovation mediate the relationship between dynamic sensing capabilities and firm competitiveness within the dynamic capabilities framework?”

It was predicted that the relationship between dynamic sensing capabilities (independent variable) and firm competitiveness (dependent variable) was mediated by Inside-In Innovation (mediating variable). Creswell and Creswell (2023) argue that the researcher may consider second order variables when establishing relationships amongst independent, dependent, and mediating variables.

3.2 Hypotheses development

3.2.1 Hypotheses

The hypotheses were developed based on the research question and are presented underpinned by the literature.

3.2.1.1 Hypothesis 1 (H_1)

Umulkher & Gichinga (2024) posits that sensing capabilities directly contributes to firm competitiveness. Additionally, other scholars have displayed similar posture that there is a link between sensing dynamics and firm competitiveness (Fainshmidt et al., 2019; Al Dhaheri et al., 2024). In support, Chowdhury and Quaddus (2021) argue that it is imperative for firms to deploy dynamic capabilities to mitigate against the risk of financial loss. Thus, it is hypothesised that:

H$_1$: Dynamic sensing capabilities positively influence firm competitiveness

3.2.1.2 Hypothesis 2 (H$_2$)

Bogers et al. (2019) argues that sensing capabilities are characterised by environmental scanning, which enables the capture of new information and the selection of opportunities, thereby facilitating the identification of emerging. In addition, Goerzig and Bauernhansl (2018) posit that these emerging opportunities necessitate internal resource investment to develop products or services that are tailored to meet customer needs effectively.

Thus, it is hypothesised that:

H$_2$: Dynamic sensing capabilities positively influence Inside-In Innovation

3.2.1.3 Hypothesis 3 (H$_3$)

Afum et al. (2021) argue that firms need to find creative ways to sustain their operations and remain competitive, suggesting that Inside-In Innovation is embedded in the broader innovation construct. Recent scholarship purport that innovation improves financial performance and firm competitiveness (Agazu & Kero, 2024; Sukumar et al., 2020; Obeidat et al., 2021). However, such companies ought to have processes and structures that foster innovation to be in a better position to compete with their peers (Sukumar et al., 2020). Thus, it is hypothesised that:

H$_3$: Inside-In Innovation positively influences Firm Competitiveness

3.2.1.4 Hypothesis 4 (H$_4$)

Teece (2020) suggests that “to remain competitive over time, a company must be able to move quickly in response to major changes in society, technology, competition, regulation, labour markets, and myriad other areas” (p. 28), and “strong dynamic capabilities enable effective open innovation practices” (p. 29). In addition, Sarwar et al. (2023) postulate that dynamic capabilities systematically solve a company’s issues through timely and market related decisions, improving and developing new organisational competencies and ensuring that it is future ready and thus generating long term competitiveness.

H$_4$: Inside-In Innovation mediates the relationship between Dynamic Sensing Capabilities and Firm Competitiveness

3.4 Control variables

According to Bartram (2021), the objective of control variables is "to minimize bias in one's estimates – but this purpose is achieved only if the controls we add are confounders, that is, variables that are causally prior to the independent variable whose impact we seek to identify" (p. 424).

3.4.1 Respondent age

According to Andrews and Hertzog (1986), age plays a critical role in surveys as older respondents tends to provide less indication of characteristics and other measurements of interest in comparison to the younger participants.

3.4.2 Respondent gender, education level

Green (1996) suggests that gender disparity in participation was due to language proficiencies driven by education levels; therefore, expecting more participation from women. However, women are under-represented in the Energy sector, estimated to be ~15% along the energy value chain in 2021 (IEA, 2023; Stats SA, 2021). Additionally, Harvey (2022) argues that highly experienced managers display more sensing capabilities in comparison to their peers, i.e., gathering insights on customer needs, competitors and technology trends.

3.4.3 Respondent management role

Pitelis et al. (2024) support this view and further argue that managers with high construal levels display stronger sensing capabilities than peers, increasing their ability to identify and respond to emerging opportunities in dynamic environments.

3.4.4 Management experience

Kucher and Zamrii (2020) acknowledge the role managers' experiences contributes in an evolving firm ecosystem. In addition, Chen et al. (2006) posits that managerial capability is one of the eight critical elements required to attain firm competitiveness.

3.4.5 Firm size

Firm competitiveness and performance are influenced by a range of contextual factors, including firm size (Daugaard & Ding, 2022; Dvouletý & Blažková, 2021; Hermundsdottir & Aspelund, 2021; Huang et al., 2023; Pundziene et al., 2022).

3.5 Conclusion

The research question, conceptual model, and hypotheses have been developed.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

The aim of the study is to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning capacity).

This chapter commences with a discussion of the research philosophy and approach deemed appropriate for the study. Thereafter, the research strategy was articulated, including population insights, the level and unit of analysis, and the sampling method used in the study. The subsequent sections present the research instrument including details on data collection, analysis tools, reliability, and validity considerations. The researcher then discusses limitations of the research design and methods applied, followed by ethical considerations used in the study inclusive of a survey questionnaire accompanied by a consent section to safeguard all parties involved including voluntary participation and anonymity guarantee.

4.2 Choice of research philosophy and approach

4.2.1 Research philosophy

Philosophical assumptions refer to the believes and values that the research upheld during the study (Creswell & Creswell, 2023). The philosophical assumptions also determine assumptions and methodology deployed in the study. This is achieved through encouraging researchers to choose a problematising review approach and encouraging reflexivity, conduct a broad but selective reading to achieve a representative sample and in-depth analysis of data (Alvesson & Sandberg, 2020).

Epistemological, ontology, and axiology assumptions were made and the researcher relied on evidence provided by the participants and ensured minimal interactions with the research subjects. Ali (2024) argues that epistemological philosophy theorises that reality can be measured and quantified objectively. In addition, ontological philosophy posits the independence of this reality and requires systematic observation and empirical investigation. Lastly, axiology philosophy supports minimisation of researcher's biases and values during the research process to enable reliability and repeatability of outcomes.

The researcher chose positivist research paradigm due to its inclination towards objectivity driven by empirical observation and logical deduction and stems from positive affirmation of anchoring theories (Ali, 2024; Kerlinger & Lee, 2000). Maksimovic and Evtimov (2023) postulate that, "the paradigm on which a methodological approach is developed, determines the situations in which its application will be most appropriate" (p. 1).

Maksimovic and Evtimov (2023) agrees that positivism aims to investigate patterns of a phenomenon and test theories. In addition, Creswell and Creswell (2023) argue that positivism paradigm reflects the need to study effects such as mediating variable that causes outcomes through hypothesis testing. In addition, Junjie and Yingxin (2022) argue that credible and meaningful data is required to determine cause and effects relationships. Hence, a survey was used to understand the relationships amongst the constructs. This also ensured that researcher maintains objectivity and does not influence data outcomes (Maksimovic & Evtimov, 2023).

Positivist philosophy assumes that universal rules can be generalised across the population without consideration of contextual considerations (Junjie & Yingxin, 2022). The researcher included research pilot phase, chose a large sample and added control variables in attempt to minimise the shortcomings of the methodology (Mack, 2010). Insights derived from the data collected tested against existing literature to ensure that the verification principle of the philosophy is upheld and minimise personal opinions of survey participants (Maksimovic & Evtimov, 2023).

4.2.3 Research Approach selected

A deductive approach was deployed to test for a relationship between dynamic sensing capabilities and firm competitiveness and mediating effect of Inside-In Innovation. The researcher applied existing theory and tested hypotheses using statistical analysis (Haque, 2022). This approach was chosen, as Maksimovic and Evtimov (2023) purport that quantitative approach denotes a positivist paradigm, and it is anchored on the establishing relationships including verifying of existing theories. Such relationship amongst the variables can be measured using instruments and statistically analysed (Creswell & Creswell, 2023).

4.3 Research strategy

The study adopted a descriptive research design utilizing a cross-sectional survey to empirically test hypotheses and examine the interrelationships among the variables under investigation (Creswell & Creswell, 2023). This methodological choice was strategically aligned with the primary objective; to assess the influence of dynamic sensing capabilities on firm competitiveness and to evaluate the mediating role of Inside-In innovation within the theoretical lenses of dynamic capabilities and open innovation (Hunziker & Blankenagel, 2024). The decision to employ a cross-sectional approach was driven by practical constraints, notably the limited timeframe available for data collection, which necessitated capturing information at a single point in time (Cvetkovic-Vega et al., 2021).

Survey designs, characterised by modified standardised questionnaires, were deliberately chosen to minimise measurement bias and facilitate the identification of causal relationships, thereby enabling statistical generalisation to the broader population (Walters, 2021). Recognising the inherent limitations of cross-sectional research, particularly its inability to establish temporal causality, the researcher implemented transparency measures and provided detailed methodological disclosures to mitigate these shortcomings (Maier et al., 2023). Consequently, the research design reflects a pragmatic yet theoretically grounded approach, balancing methodological rigour with contextual constraints to advance understanding of dynamic sensing capabilities and their strategic implications.

4.3.1 Population

The study aims to determine the influence of dynamic sensing capabilities on firm competitiveness and the mediation role of Inside-In Innovation. Population denotes the group of people or companies that the study is focusing on, and the study outcomes can be implied towards them (Hossan et al., 2023). The population in this study was individuals working for South African energy companies. This included upstream, midstream, and downstream employees estimated to be 120 000 (EIA, 2023). Only individuals above the age of 18 were considered due to the legal employment age in South Africa. However, due to impractically of collecting data from the entire population, a sample was selected for representation (Walters, 2021).

4.3.2 Sampling design, frame and/or criteria

Purposive sampling, a non-probability sampling method was deployed where the researcher made judgement on selecting participants who possess specific characteristics or knowledge relevant to the theoretical constructs under study for participation (Memon, 2025). Predefined criteria were used to ensure that employees in the energy sector participated in the research. The researcher made use of her professional network to identify initial participants. Purposive sampling was then combined with snowball sampling to acquire additional participants that are hard to reach through conventional methods, through referrals to ensure sufficient dataset for analysis. Although the two sampling methodologies, when used together, are ideal for sectors such as the energy industry - where people are hesitant to share information without personal relationships - and are cost-effective and practical, this approach introduces selection bias.

To reduce biases, the study deployed maximum variation sampling to individuals employed in the energy sector to ensure that broader spectrum of insights is captured. This was achieved through articulation and selection of participants based on the size of the firms they work for, roles, experience and demographic attributes to ensure robustness of the study. Therefore, the researcher invited participants across the traditional and new energy value chains and survey accessed through multiple online platforms.

Mecer et al. (2017) argue that demographic attributes alone cannot reduce selection bias in nonprobability surveys but required exchangeability, positivity and composition. Hence, the study furthermore tested for exchangeability in ensuring that variables are not confounders and can serve as proxies for confounders due to their proximity correlation to confounders to reduce bias. Positivity refers to underrepresented but present groups to be weighted up in the data collected, but if the group is entirely absent, theoretical justification is required. Lastly, sample composition was deliberately managed to match target population, including post data collection adjustments.

The sampling frame refers to the “set of units from which the sample is drawn” (Hossan et al., 2023: 213). The scholars argue that the sample frame must be able to provide all the required information as per the survey instrument. The sampling frame consisted of individuals responsible for making strategic and technical decisions in the South African energy companies. The sample was the number of cases chosen from the sample frame. The required sample size for the study was calculated to be 383 (see Annexure A). The initial participants invited to take part in the survey were encouraged to disseminate it to their contacts within the energy sector.

4.3.3 Level and unit of analysis

In this study, the level of analysis is 'individuals'. According to Hossan et al. (2023), unit of analysis refers to "individuals who provide a conclusion to understand and resolve research questions" (p. 210). Individuals in management and technical roles responsible for making strategic and technical decisions in the energy sector in South Africa were targeted for responses to the survey.

4.4 Measurement instrument

The study adopted existing tools to assess, and measure identified constructs. Dynamic sensing capabilities as a micro foundation of dynamic capabilities is measured using environmental scanning and opportunity selection, which are first order constructs (Teece, 2020; Pundziene et al., 2022). Inside-In Innovation was measured with an adopted and validated scale using five items and modified to include additional items (Pundziene et al., 2022; Farzaneh et al., 2022). These items include communication loop, employees' collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning capability.

Lastly, firm competitiveness was measured using an adopted and validated five-item scale, which was modified to include two additional items (Mikalef & Pateli, 2017). These items are sales growth including comparison to competitors, product volumes, quality, market share, and costs. A 5-point Likert scale was adopted from existing scales and deployed to measure each item of the three constructs using scores as it provides balance between cognitive and granularity, ranging from "1 (I do not agree) to 5 (strongly agree)".

4.4.1 Dependent variables

The dependent variable was firm competitiveness and was measured using an adapted and validated five-item scale, which was modified to include two additional items

(Mikalef & Pateli, 2017). These items are sales growth including comparison to competitors, product volumes, quality, market share, and costs.

4.4.2 Independent variables

Dynamic sensing capabilities, an independent variable, was measured with adopted and validated scale of two reflective first order factors, that is, environmental scanning and opportunity scanning. Environmental scanning was measured using six items (Pundziene et al., 2022). The items related to environmental scanning focused on determining whether, on a regular basis: local and international market trends are assessed; technology developments are followed; and customers' experiences and emerging needs were assessed. The last two items focused on: understanding if enough time was spared to observe and evaluate business environment; and if forthcoming environmental changes were noticed early. Opportunity selection was measured using three items (Pundziene et al., 2022). These items focused on understanding: whether there was an orientation towards high-value financial projects even if the projects are risky; bold strokes were taken when searching for new opportunities; and whether new and original ideas were encouraged in the organisation.

4.4.3 Mediating variables

The mediating variable was Inside-In Innovation and was measured with an adopted and validated scale using five items and modified to include an additional item (Pundziene et al., 2022). These items include communication loop, employees' collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning capability.

4.4.4 Control variables

Control variables were demographic data, respondent educational information, work experience, management role, industry type, firm size, and age. Objectives of these control variables were to ensure that respondents represent targeted population.

4.5 Data collection

Power analysis was done to understand how many respondents were required based on the target population (Russo & Stol, 2023). The mean, standard deviation, and skewness were determined using the R package cSEM.

4.5.1 Online Survey

Qualtrics online survey platform was self-administered to collect data. This provided ease of access and data entry, broad coverage of qualifying participants across the energy sector, low costs, and ensuring that participants address all questions asked (Evans & Mathur, 2018). The survey questionnaire was distributed using the Qualtrics link through email, WhatsApp, and LinkedIn to personal network contacts that qualify. Though the risk of spam perception was mitigated by inclusion of both the researcher's and the supervisors' email addresses, some respondents still verified with the researcher if the link was valid due to increased cyber security threats.

Each contact was asked to forward the questionnaire to their contacts who meet the criteria. The target was to at least distribute the survey to at least 383 potential participants to ensure sufficient response rate. Granting respondents anonymity also meant that the researcher cannot determine if respondents have filled the survey multiple times or not.

4.5.2 Survey pre-test

The survey pre-test was sent to 20 individuals through email to test if the questionnaire is clear and understandable. The survey pre-test was issued on the 26th of July 2025 and concluded on the 8th of August 2025. The intent was to use feedback to improve the questionnaire prior to being issued to the respondents. The data collected during this phase was also used for reliability test. 14 responses were obtained from participants on management-level from South Africa's energy sector. There were two outliers where demographic questions were asked; one respondent disclosed their name and the other their race on the text boxes which were under the opening statement. The researcher has since removed all unnecessary text boxes to ensure that only data provided is linked to the questions asked.

Data screening confirmed that there were no duplicates and negligible missing answers (0.01%). The mean for completion time was ~20.5 minutes, with only one respondent flagged for atypically fast, non-differentiated responses and this data point was removed from further analysis. Overall, participants answered all questions, demonstrating a fair understanding of what was required. One of the participants raised a concern regarding question C3.6.1: “Employees are proficient in project management” as it seemed to suggest that all employees need to be proficient in project management. The question was changed to: “Employees working on projects are proficient in project management.”

Microsoft Excel was used for descriptive statistics and showed balanced distributions (mean ≈ 3.0, SD ≈ 1.24). The scale sensitivity was checked to see if too many responses are not clustered around the lower scale (1 lowest option), or the highest option (5). 14% was found to be at the lower scale and 10% at the highest scale which means most people used the whole scale, indicating healthy item variability. Reliability testing across all constructs demonstrated strong internal consistency. Cronbach’s alpha values ranged from 0.86 to 0.95, comfortably above the 0.70 threshold. Sections 12–14 showed very good reliability ($\alpha \approx 0.86$–0.89), while Sections 15–19 showed excellent reliability ($\alpha \geq 0.93$). The very high alphas (>0.90) suggested excellent internal consistency, though some redundancy among items may be present.

Overall, the pilot analysis indicated that the survey instrument was robust and reliable with no major threats from missing data, response bias, or weak items. Early validity checks supported that the constructs were well-defined. Based on these findings, the instrument was deployed in the main study, with minor refinements recommended to flagged items for clarity and to reduce redundancy.

4.6 Survey distribution

The survey was distributed on email, WhatsApp, and LinkedIn on August 21, 2025, and it was intended to close on September 20, 2025. Nonetheless, a low response rate prompted the research to extend the timeline to October 4, 2025. It should be noted, however, that this period is one of the busiest in the Energy sector due to various conferences being sequenced during this time of the year, as pointed out by one of the respondents. A total of 128 responses were recorded during this phase and 107 usable data remained after screening.

4.7 Data storage and Retention

Data storage and retention in an accessible format is critical for a research project. The researcher used Microsoft OneDrive to store data and ensure backup, recovery, and ensuring that permission is appropriately managed. The data will be stored for a minimum of 10 years and the researcher is responsible to ensure that the data is safely stored.

4.8 Data preparation

4.8.1 Data screening

128 data points were recorded during the survey. The removal of incomplete surveys resulted in 107 datasets remaining. These were taken through a screening process which included the following:

- Entries marked as previews, partial completions, or test submissions were excluded.
- To maintain data quality, speeding responses or those completed in under three minutes (180 seconds) were removed, as such rapid completion suggested low engagement or careless responding.
- The dataset was checked for respondents who gave the same rating across all questions. These cases, which showed no variation in their answers, were removed to ensure that only meaningful and engaged responses were included in the analysis.

Application of the screening process resulted in 104 valid cases for analysis. This effective sample size met the recommended thresholds for R package cSEM, ensuring adequate statistical power and model stability.

4.8.2 Data preparation

Following data screening, the dataset was prepared for modelling by (i) standardising variable labels, (ii) converting Likert responses to numeric scores, (iii) organising items into theoretically defined constructs, (iv) handling missing values, and (v) deriving composite scores required for the two-stage R package cSEM hierarchy.

4.8.2.1 Variable standardisation and labelling

The original questionnaire headers were long and descriptive. For analytical clarity and to reduce coding errors, item labels were shortened to construct-item codes (e.g., ES1–ES5 for Environmental Scanning, OS1–OS5 for Opportunity Selection, FC1–FC6 for Firm Competitiveness, etc.). This retained a one-to-one mapping with the instrument while enabling reproducible scripting.

Table 3: Coding for the constructs

Variable	Description	Variable Type	Level in HCM	Items	Data Type
DSC	Dynamic Sensing Capabilities (overall)	Independent	Second-order composite	2 (blocks)	5-point Likert (treated as interval)
ES	Environmental Scanning (e.g., ES1–ES5)	First-order	Part of DSC	5	5-point Likert
OS	Opportunity Selection (OS1–OS5)	First-order	Part of DSC	5	5-point Likert
III	Inside-In Innovation (overall)	Mediator	Second-order composite	6 (blocks)	5-point Likert
CL	Communication Loop (CL1–CL5)	First-order	Part of III	5	5-point Likert
EC	Employee Collaboration (EC1–EC5)	First-order	Part of III	5	5-point Likert
NI	New Ideas / Idea Climate (NI1–NI5)	First-order	Part of III	5	5-point Likert
KAS	Knowledge & Assets Sharing (KAS1–KAS10)	First-order	Part of III	10	5-point Likert
IIP	Innovation Implementation Process (IIP1–IIP5)	First-order	Part of III	5	5-point Likert
OLC	Organisational Learning Capability (OLC1–OLC5)	First-order	Part of III	5	5-point Likert
FC	Firm Competitiveness (FC1–FC6)	Dependent	Single-order composite	6	5-point Likert

Demographic and control variables were included for descriptive profiling and contextual interpretation of the sample. Age and education were treated as ordinal variables, while gender, role, sector, and value-chain position were nominal. Missing or inconsistent demographic responses were cleaned using category consolidation rules (responses with fewer than four instances were grouped under “Other”).

Table 4: Coding for the control variables

Variable	Description	Variable Type	Level in HCM	Items	Data Type
Age	Respondent's age group (e.g., 18–24, 25–30, etc.)	Descriptive/ profile	—	1	Categorical (ordinal)
Gender	Respondent's self-identified gender (Male, Female, Other)	Descriptive/profile	—	1	Categorical (nominal)
Education	Highest level of education attained (e.g., Matric, Diploma, Bachelor's, Master's, Doctorate)	Descriptive/profile	—	1	Categorical (ordinal)
Work Experience	Total number of years of professional experience	Descriptive/profile	—	1	Categorical (ordinal)
Role	Current professional role or title (selected choice or custom text)	Descriptive/profile	—	1	Categorical (nominal)
Nature of Role	Primary nature of work (e.g., technical, managerial, analytical, operational)	Descriptive/profile	—	1	Categorical (nominal)
Company Size	Approximate organization size (e.g., Small, Medium, Large)	Descriptive/profile	—	1	Categorical (ordinal)
Company Sector	Sector or industry in which the respondent's company operates (e.g., Energy, Manufacturing, Services)	Descriptive/profile	—	1	Categorical (nominal)
Energy Value-Chain Play	Position in the energy value chain (e.g., Upstream, Midstream, Downstream, Services)	Descriptive/profile	—	1	Categorical (nominal)

4.8.2.2 Likert conversion

All agreement-scale responses were converted from text labels (e.g., "4- Agree") to numeric scores 1–5. This ensured consistent treatment across constructs and enabled computation of reliabilities, AVE, and structural paths.

4.8.2.3 Construct organisation

Items were grouped into nine first-order constructs consistent with the research model: ES, OS, FC, CL, EC, NI, KAS, IIP, and OLC. These first-order constructs later feed into higher-order composites (DSC and III) in the structural stage.

4.8.2.4 Missing data handling

After conversion, case wise deletion was applied at the construct-score stage to ensure complete data for R package cSEM bootstrapping. This yielded the effective modelling sample of 107 responses from the originally captured 128.

4.8.2.5 Composite scores for the two-stage HCM

Unit-weighted means were computed for each first-order construct (ES, OS, FC, CL, EC, NI, KAS, IIP, OLC). These scores served as indicators for the higher-order components (DSC, III) and the structural paths in Stage 2.

4.8.2.6 Checking the Response Time of Respondents

To reduce careless responding, we screened survey duration and extremely uniform answering:

- Speeders: Qualtrics' duration (in seconds) was used to flag unrealistically fast completions. Following common practice for ~40–60 items, responses under 180 seconds (3 minutes) were excluded by rule.
- Straight-liners: We computed each respondent's within-person SD across all Likert items and removed cases with SD ≤ 0.15 (i.e., near-constant responding).
- Preview/test rows: Submissions labelled Survey Preview or Preview and those with Progress < 100% were dropped.

After these quality checks and standard preprocessing, 104 complete and usable cases remained for R package cSEM.

4.8.2.7 Data Grouping and Enrichment

- Likert conversion: Qualtrics exports (e.g., "4 – Agree") were converted to numeric 1–5 (leading digit extraction) for analysis.
- Label standardization: Long item labels were programmatically shortened to ES1–ES5, OS1–OS5, FC1–FC6 to ensure reproducible scripting.
- Demographic consolidation: For Work title/Role and Nature of role, we merged "Selected Choice" with corresponding "Other – Text" entries.
- Rare-category pooling: To keep demographic tables interpretable, custom/open responses with fewer than 4 occurrences were grouped into "Other"; recurring custom responses (≥4) were elevated to their own category.
- Treatment of scales: All multi-item constructs were modelled as composites; reliability (Cronbach's α, Composite Reliability) and convergent validity (AVE) were first confirmed at the block level (Stage-1).

4.8.2.7 Outlier Analysis and Robustness Check

Outliers were assessed to ensure data quality and verify that extreme response patterns did not unduly influence model estimation. Due to all items in the survey measured on a bounded five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), large numerical outliers were not expected. However, statistically extreme values can still occur when most respondents cluster tightly around a particular rating (e.g., 4 = Agree), making infrequent ratings (e.g., 1 or 2) appear as outliers under standard distributional rules.

To systematically identify such cases, the interquartile range (IQR) criterion was applied at the item level. Each indicator's first (Q1) and third (Q3) quartiles were computed, and any observation below Q1 − 1.5×IQR or above Q3 + 1.5×IQR was flagged as an outlier. This procedure was automated in R across all constructs, including Environmental Scanning (ES1–ES5), Opportunity Selection (OS1–OS5), Firm Competitiveness (FC1–FC6), and the Inside-In Innovation dimensions (Communication Loop, Employee Collaboration, New Ideas, Knowledge & Asset Sharing, Innovation Implementation Process, and Organisational Learning Capability).

Outlier detection was done on the full item-level dataset which initially contained 107 respondents. The R script identified 35 out of 107 cases (32.7%) as potential outliers across at least one indicator. These cases were flagged because their responses fell outside the interquartile range for one or more items, not because of invalid or erroneous input. In bounded Likert data, such as "statistical outliers" typically represent extreme but legitimate opinions, such as respondents who consistently disagreed with most items when the majority agreed.

4.9 Research quality and rigour

The measurement model was assessed to confirm the reliability and validity of the latent constructs before proceeding to structural analysis. In line with R package cSEM guidelines, reliability was evaluated through Cronbach's alpha (α) and Composite Reliability (CR), while Convergent Validity was assessed using the Average Variance Extracted (AVE).

Table 5: Assessment of the measurement model

	Construct	Alpha	CR	AVE	k
	<chr>	<dbl>	<dbl>	<dbl>	<int>
1	ES	0.781	0.852	0.535	5
2	OS	0.777	0.852	0.539	5
3	FC	0.754	0.835	0.46	6
4	CL	0.873	0.908	0.663	5
5	EC	0.893	0.922	0.703	5
6	NI	0.895	0.922	0.703	5
7	KAS	0.934	0.945	0.633	10
8	IIP	0.846	0.896	0.635	5
9	OLC	0.845	0.89	0.619	5

4.9.1 Reliability

Sürücü and Maslakci (2020) defines reliability as "an indicator of the stability of the measured values obtained in repeated measurements under the same circumstances using the same measuring instrument" (p. 2695). The reliability of the adapted survey instrument was tested during piloting phase where reasonable responses were gathered from the target sample and internal Cronbach's alpha values range determined to check adequacy and appropriateness of internal reliability (Sarwar et al., 2023). The researcher also tested for internal consistency through composite reliability test which found to be 0.7 and higher in line with literature for internal consistency (Hair et al., 2012). Similarly, all Composite Reliability (CR) values exceeded the 0.70 benchmark, confirming that the measurement items consistently represented their respective latent variables.

4.9.2 Convergent Validity

Sürücü and Maslakci (2020) defines validity as "concerned with whether the measuring instrument measures the behaviour or quality that it is intended to measure and is a measure of how well the measuring instrument performs its function" (p. 2695). Hence, the study deployed scales that have been validated by esteemed scholars in the field.

Henseler et al. (2015) claim that discriminant validity test verifies that measures deployed to measure a construct reaches such objective without being acquired by other measures.

Convergent validity was examined using Average Variance Extracted (AVE), which measures the proportion of variance explained by the construct relative to the variance due to measurement error. All constructs recorded AVE values above 0.50, demonstrating that the indicators shared enough variance in explaining their respective latent constructs.

The results, therefore, confirm that the measurement model meets the minimum criteria for reliability and convergent validity.

The reliability analysis confirmed that constructs were internally consistent, with Cronbach's alpha and Composite Reliability values above 0.70. Convergent validity was supported, as all constructs achieved AVE values exceeding 0.50 except for Firm Competitiveness (0.46), which remained acceptable due to a high CR value (0.835). These results confirm that the measurement model was reliable and valid for further structural analysis.

4.10 Data analysis approach

Creswell and Creswell (2023) argue that Structural Equation Modelling (SEM) is a correlational design which measures a degree of association amongst complex variables in the model. The analysis utilised R package Composite-based Structural

Equation Modelling (cSEM) with bootstrapping (5,000 resamples) based on practical reliability and methodological rigour, implemented in the cSEM package, i.e., R version 4.5.1 (current CRAN version at the time of analysis).

This approach was chosen because it is covariance-based, prediction-oriented, and robust to non-normal data, making it suitable for the study's moderate sample size, handles both reflective and formative contructs, and provides higher composite reliability and composite validity as opposed to covariance-based Structural Equation Modelling (Hair et al., 2017). The two software are comparable on discriminant validity and beta coefficients.

4.10.1 Descriptive analysis

Descriptive statistics was done as an initial step in software of R-package cSEM to gain insights, i.e., trends, patterns, and correlations between variables in the dataset, allowing researcher to make informed decisions about the appropriate statistical technique for the study (Alabi & Bukola, 2023).

The overview included means, standard deviations, and internal consistency reliabilities between study variables. The mean is the arithmetic average of the dataset and one of the measures of central tendency. Standard deviation is one of the variability indices which provides the spread of the dataset. The normality tests were also done, i.e., skewness to show asymmetry of data distribution and kurtosis provides 'tailedness' of data distribution through quantification of outliers. Normal data distribution is proven when kurtosis and skewness' values range between +3 to −3 (Aburumman et. al., 2023). In this section, an overview of descriptive statistics for the three constructs, i.e., dynamic sensing capabilities, Inside-In Innovation, and firm competitiveness constructs are provided.

A two-stage R-package cSEM procedure was used:

4.10.2 Model measurement assessment

According to Aburumman et al. (2022), the measurement model (outer model) describes the relationship between a latent variable and its indicators or relationship between observable and underlying constructs. This ensures that the objective of the survey items is achieved, and that the survey instrument is valid and reliable. Therefore, the internal consistency reliability, i.e., cronbach's alpha (CA) and composite reliability (CR), convergent validity and discriminant validity were determined, and results are presented in chapter 5.

4.10.2.1 The internal consistency reliability, i.e., cronbach's alpha (CA) and composite

For each first-order block (ES, OS, CL, EC, NI, KAS, IIP, OLC, FC), Cronbach's α, Composite Reliability (CR), and AVE were computed and confirmed acceptable thresholds (α/CR ≥ .70; AVE ≥ .50, with FC acceptable on CR even if AVE was slightly lower).

4.10.2.2 Convergent validity and AVE were computed and confirmed acceptable thresholds (α/CR ≥ .70; AVE ≥ .50

4.10.2.3 Discriminant validity

Stage-1 (Measurement checks): For each first-order block (ES, OS, CL, EC, NI, KAS, IIP, OLC, FC), Cronbach's α, Composite Reliability (CR), and AVE were computed and confirmed acceptable thresholds (α/CR ≥ .70; AVE ≥ .50, with FC acceptable on CR even if AVE was slightly lower).

4.10.3 Structural measurement analysis and hypotheses testing

According to Aburumman et al. (2022), the structural model assessment aims to examine the predictive capabilities of model and the relationships between constructs. The assessment of the structural model included coefficient of determination (R^2), cross-validated redundancy (Q^2), effect sizes (f^2), and path coefficients (hypotheses testing). The analysis for the structural model were as follows:

4.10.3.1 Coefficient of determination (R^2)

The values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak for R^2.

4.10.3.2 cross-validated redundancy (Q^2),

while values greater than zero are considered meaningful for Q^2.

4.10.3.3 Effect sizes

In addition, values of 0.35, 0.15, and 0.02 are considered large, medium, and small for effect sizes (f^2).

4.10.3.4 Hypotheses testing

Therefore, Structural model: Unit-weighted block scores for each first-order construct were created; higher-order composites were then specified as:

- DSC ← ES + OS
- III ← CL + EC + NI + KAS + IIP + OLC
- FC←FCs

Structural paths tested: III ~ DSC and FC ~ DSC + III. Inference used bootstrapping (5,000 resamples) with path coefficients (β), t-values, p-values, and R^2 reported.

Two steps are required to examine the path coefficients (hypotheses testing), i.e., the p-value is required to be <0.05 and secondly, the confidence interval must be zero and not cross. If these two steps were met, then the path or hypothesis was considered statistically supported.

Detailed results are reflected in chapter 5 commencing with the demographic data of the respondent is contextualised, followed by a discussion of results from R-package cSEM which is a variance-based method, as discussed earlier in this chapter. These results were divided into three parts, i.e., descriptive analysis; model measurement assessment; and structural measurement assessment. Hypotheses assessment included bivariate relationship testing of independent, dependent, and mediation variables.

4.11 Limitations of the research design and methods

Wang and Cheng (2021) cautions that cross-sectional surveys by nature considers data at one specific point in time and it is problematic to determine causal relationships from the analysis as there are no prospective or retrospective follow-up. These surveys are prone to non-response, multiple participation, and recall biases. The researcher assumed that the target population had access to email, WhatsApp, and LinkedIn. The validity of the responses may be questioned as it relies on the respondents’ views and perceptions. The researcher only conducted quantitative study and therefore the study lacks qualitative data to supplement the finding with the depth of concepts.

4.12 Ethical considerations

Creswell and Cresswell (2023) purport that ethical issues should be anticipated throughout the study and solutions developed, due to the nature of study involving data collection from and about people. An objective was to study influence of dynamic sensing capabilities on the firm's competitiveness and the mediation role of Inside-In Innovation. The population identified for the study is the South African energy companies represented by individuals.

An informed consent letter which is a legal document that protects all parties involved in the study was attached to the survey questionnaire. The survey was conducted in English, a business language in South Africa. The description and purpose of the study were briefly explained, and all participants guaranteed the anonymity (Sarwar et al., 2023). Participation was voluntary and GIBS research protocols adhered to throughout the study. The survey included questions regarding demographic data of the respondents such as age, gender, education, department, job position, and experience to ensure suitability of sample participation (See Annexure C). The ethical clearance application was submitted electronically to the ethics committee for approval prior to data collection (See Annexure B).

4.13 Conclusion

This chapter has articulated the philosophical assumptions, research philosophies, approach, design and methods to be deployed to ensure integrity of the research. It has further provided insights on ethical considerations of the study.

CHAPTER 5: RESULTS

The aim of the study was to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning).

The study commenced with an introduction in Chapter 1, providing motivation for research. The foundation of the research was established by interrogating the latest literature on the research constructs, their relationships, and the conceptual model presented in Chapter 2. The research question and emerging hypotheses were discussed in Chapter 3. The Research methodology presented in Chapter 4.

In this chapter, results from the study are presented in four parts.

- The first part of the results focused on demographic data analysis of the respondents.
- The second part of the results focused on descriptive analysis of our main constructs and Inside-In Innovation variables.
- The third part presents the model measurement assessment.
- The fourth part of the results focused on the structural measurement assessment and hypotheses testing to understand the relationship between dynamic sensing capabilities (independent variable), Inside-In Innovation (mediating variable) and firm competitiveness, i.e., Hypotheses assessment (H_1, H_2, H_3 and H_4) excluding and including control variables plus sensitivity analysis.

5.1 Demographic data analysis

The sample consisted of 104 valid cases that were used for the analysis after data cleanup, explained in the data preparation in Chapter 4. The demographics below are divided into basic, socio-economic, and organisational demographics.

5.1.1 Basic demographics

The gender distribution in the sample was uneven, favourable to male participants with 58% and 42% identifying as female. ~81% of the respondents were in the age category 35-54 with no representation in the 18-24 years old. Despite employment equity efforts in the South African labour market, women remain under-represented, and the Energy sector is no exception to the trend, with women representation estimated to be ~15%

along the energy value chain in 2021 (IEA, 2023; Stats SA, 2021). Though companies expressed intent to improve at the time, 42% seems rather higher than expected considering that only 4 years has passed since the report was issued and could potentially be associated with selection biases in purposive sampling which relied on the researcher's personal and professional network within the sector. This is further supported by missing age group in the respondents as the reason could be that they are still in universities, are new to the job market, or are outside the researcher's network.

Table 6: Basic demographics data analysis

Gender	Number of responses	Percentage (%)
Female	45	43%
Male	58	56%
Prefer not to say	1	1%
Age, in years	Number of responses	Percentage (%)
<18	0	0
18-24	0	0
25-34	8	7.7
35-44	46	44
45-54	38	37
>55	12	12

5.1.2 Socioeconomic demographics

In terms of work experience, most of the respondents had more than 10 years of work experience, i.e., 93% and above. 45% of these individuals had more than 20 years industry experience. This coincides with 72% being in management roles and executive roles focusing on strategic issues and remainder of the respondents focused on technical roles. This is supported by their educational levels with 93% of the respondents who have honours degrees or higher, with majority having master's degree qualifications. Absence of respondents with no formal or matric qualification supports the missing ages groups discussed in the previous section. In addition, Harvey (2022) argues that highly experienced managers display more sensing capabilities in comparison to their peers, i.e., gathering insights on customer needs, competitors, and technology trends. Therefore, the sample profile fits the study.

Table 7: Socioeconomic demographic analysis

Education levels	Number of responses	Percentage (%)
No formal education	0	0
Matric or equivalent	0	0
Diploma	1	1
Bachelor's degree	7	7
Honours	28	27
Master's degree	59	57
Doctorate or higher	9	8.7
Work experience, in years	Number of responses	Percentage (%)
0-4	2	2
5-9	5	5
10-15	20	19
16-20	30	29
>20	47	45
Work titles/ roles	Number of responses	Percentage (%)
Manager	30	29
Senior Management	30	29
Executive	15	14
Other	29	28
Work titles/ roles	Number of responses	Percentage (%)
Technical	30	29
Strategic	62	60
Other	12	12

5.1.3 Organisational demographics

Most of the respondents in Table 7, i.e., 85% work for companies classified under the energy sector while the remainder of respondents fall under parts of the energy value chain. However, discrepancy exists, as no respondent chose an integrated energy value chain as their energy value chain play; instead, they were specific that they work for upstream, midstream, or downstream with almost equal distribution amongst the three. 61% of the respondents work for companies with more than 5000 employees. The sample was compared with the population in terms of firm size, as firm-level dynamics can mediate or moderate firm competitiveness (Pundziene et al., 2022). Though the distribution of size and age is ideal in this context, it is notable that the results deviated from expectations as the coal value chain is ~89% dominated by Eskom and Sasol, while the remainder is an equal split between renewables and nuclear (IEA, 2023; Akinbani et al., 2021). This discrepancy is due to the sample selection bias that surfaced due to purposive and snowballing and relied on personal and professional networks.

Table 8: Organisational demographic analysis

Company size	Number of responses	Percentage (%)
0-500	19	18
501-5000	22	21
>5000	63	61
Company sector	Number of responses	Percentage (%)
Energy	88	85%
Other	15	15%
Energy value chain play	Number of responses	Percentage (%)
Upstream	33	32
Midstream	31	30
Downstream	40	38

5.2 Descriptive statistics

Descriptive statistics was done as an initial step in R Core Team (2025) using the cSEM package to gain insights, i.e., trends, patterns, and correlations between variables in the dataset, allowing researcher to make informed decisions about the appropriate statistical technique for the study (Alabi & Bukola, 2023). The objective of descriptive statistics is to provide a clear summary of the dataset before conducting the main inferential analysis.

Table 8 below shows descriptive statistics of the data which includes means, standard deviations, and internal consistency reliabilities between study variables. The mean is the arithmetic average of the dataset and one of the measures of central tendency. Standard deviation is one of the variability indices which provides the spread of the dataset.

The normality tests were also done, i.e., skewness to show asymmetry of data distribution and kurtosis provides 'tailedness' of data distribution through quantification of outliers. Normal data distribution is proven when kurtosis and skewness' values range between +3 to −3 (Aburumman et. al., 2023). However, the R-package cSEM model does not require strict multivariate normality, unlike covariance-based SEM (CB-SEM). Reporting skewness and kurtosis is still important because it supports transparency in describing data behaviour and ensures bootstrapping results are reliable, since R-package cSEM relies on resampling rather than normal-theory assumptions.

In this section, an overview of descriptive statistics for the three constructs, i.e., dynamic sensing capabilities, Inside-In Innovation and firm competitiveness constructs are provided.

Table 8: Descriptive analysis

	Mean	Standard deviation (SD)	Skewness	Kurtosis
ES1	4.093458	0.87451	-1.35291	2.655642
ES2	4.037383	0.823307	-0.77142	0.301019
ES3	3.943925	0.919719	-0.97182	0.894471
ES4	3.71028	0.94179	-0.54464	-0.30951
ES5	3.654206	1.028855	-0.56787	-0.30234
OS1	3.240741	1.040043	-0.14072	-0.80119
OS2	3.305556	0.980733	-0.10229	-1.00686
OS3	3.722222	0.92558	-0.62235	-0.15257
OS4	3.518519	0.961711	-0.36433	-0.69293
OS5	3.439252	1.108948	-0.34159	-0.85137
FC1	3.165138	0.938022	0.138182	-0.8414
FC2	2.779817	0.926541	0.373781	-0.41924
FC3	2.953704	1.035665	0.1913	-0.70004
FC4	3.055556	0.92558	0.031571	-0.35442
FC5	2.953271	1.049557	0.140491	-0.88417
FC6	3.284404	1.2479	-0.23135	-1.11443
CL1	3.018868	1.004572	-0.14888	-1.11971
CL2	3.000000	1.090266	-0.12981	-1.13475
CL3	3.224299	1.11006	-0.23981	-0.81009
CL4	3.130841	1.046865	-0.11273	-0.90466
CL5	3.066667	1.040217	-0.33454	-0.65295
EC1	3.009346	0.995228	-0.35974	-0.84358
EC2	3.140187	1.161071	-0.34268	-0.94147
EC3	2.971963	1.193204	-0.01267	-1.09107
EC4	3.028037	1.050229	-0.05516	-0.99331
EC5	2.962617	1.008691	-0.19942	-0.65438
NI1	3.141509	1.0089	-0.39201	-0.5937
NI2	2.858491	1.055044	0.039508	-0.9922
NI3	2.914286	1.010657	-0.10718	-0.67839
NI4	3.057143	1.045398	-0.36265	-0.97683
NI5	3.247619	1.089998	-0.49555	-0.84847
KAS1	3.169811	1.018605	-0.28581	-0.8371
KAS2	3.214953	1.02817	-0.17475	-0.8325
KAS3	3.367925	1.017237	-0.50374	-0.18477
KAS4	3.411215	1.098483	-0.47403	-0.58817
KAS5	3.152381	0.988209	-0.36317	-0.56104
KAS6	3.130841	1.028684	-0.31139	-0.68453
KAS7	3.084906	0.947356	-0.23377	-0.30532
KAS8	3.084112	1.001146	0.057069	-0.50283
KAS9	2.981308	0.971104	-0.02443	-0.56604
KAS10	3.084906	0.93725	-0.02932	-0.43415
IIP1	3.235849	0.889643	-0.55188	-0.59345
IIP2	3.132075	0.976636	-0.32333	-0.50764
IIP3	3.134615	0.955898	-0.20104	-0.65563
IIP4	3.07619	1.106756	-0.06438	-0.82691
IIP5	3.653846	1.040624	-0.81793	0.194488
OLC1	3.688679	0.865896	-0.93397	1.198465
OLC2	3.514286	1.084101	-0.70909	-0.27074
OLC3	3.409524	1.006663	-0.42657	-0.39541
OLC4	3.288462	1.001679	-0.30548	-0.5881
OLC5	3.47619	0.951671	-0.59553	-0.1773

5.2.1 Dynamic sensing capabilities (DSC)

For analytical clarity and to reduce coding errors, the following construct-item codes were used for environmental scanning, i.e., ES1-ES5 and for opportunity scanning OS1-OS5 were used. The descriptive analysis are as follows for ES and OS: mean of 3.65-4.09 and 3.24-3.72 respectively indicate that respondents hold strong positive perceptions. The standard deviation of 0.82-1.02 and 0.92-1.12 respectively shows moderate variability around the mean. The skewness of -1.35 and -0.54 for ES indicating moderate negative skew leaning towards high numbers; and -0.62 and -0.10 for OS showing near symmetry. kurtosis values of -0.30 and 2.66 for ES and -1.00 and -0.15 for OS, both showing flatter curves. Both variables deviate from normality which supports appropriateness of cSEM that does not require normality.

5.2.2 Firm Competitiveness (FC)

For analytical clarity and to reduce coding errors, the following construct-item codes were used for firm competitiveness, i.e., FC1-FC6 were used. The descriptive analysis of DSC is in Table 9 below. The descriptive analysis are as follows for the FC variables: 2.77-3.28 for the mean indicating respondents show generally neutral perceptions. The standard deviation of 0.93-1.24 suggests moderate variability leaning towards higher scores in the 5-point Likert scale. The skewness and kurtosis values indicate that data distribution is approximately symmetric ranging from -0.23 to 0.37 and -1.11 to -0.35, respectively.

5.2.3 Inside-In Innovation

For analytical clarity and to reduce coding errors, the following construct-item codes were used for Communication loop: CL1-CL6; Employee collaboration: EC1-EC6; New ideas: NI1-NI6; Knowledge and assets sharing: KAS1-KAS10; Innovation investment and processes: IIP1-IIP5; and Organisational learning capability: OLC1-OLC5 were used.

5.2.3.1 Communication loop

The descriptive analysis are as follows for the CL variables: 3 – 3.22 for the mean indicating that respondents have neutral to slightly positive perceptions towards the construct. The standard deviation of 1.00 – 1.09 showing moderate variability of responses and dispersion around the mean. The skewness and kurtosis values range from -0.33 to -0.11 and -1.13 to -0.65 respectively indicating that the data distribution is approximately symmetric, with only a slight tendency toward higher scores.

5.2.3.2 Employee collaboration

The descriptive analyses are as follows for the EC variables: 2.97 – 3.14 for the mean indicating that respondents hold generally neutral perceptions. Standard deviation of 0.99 – 1.19 shows responses are sufficiently dispersed around the mean to support meaningful statistical analysis. The skewness and kurtosis values range from -0.36 to -0.05 and -1.09 to -0.65, respectively shows symmetric data distribution with slight tendency toward higher scores and have adequate discriminatory power, enabling further statistical analysis.

5.2.3.3 New ideas (NI)

The descriptive analysis are as follows for the NI variables: 2.85 – 3.24 for the mean indicates neutrality in responses. However, the standard deviation of 1.01 – 1.09 suggests moderate variability and dispersion around the mean, leaning towards higher scores in the 5-point Likert scale. The skewness and kurtosis values indicate that data distribution is approximately symmetric and flatter than normal, ranging from -0.49 to 0.04 and -0.99 to -0.59 respectively. The construct retains adequate discriminatory power to distinguish itself from other constructs.

5.2.3.4 Knowledge and assets sharing (KAS)

The descriptive analysis are as follows for the KAS variables: 2.98 – 3.41 for the mean, suggesting neutral to slightly positive perceptions towards KAS variables. Standard deviation of 0.94 – 1.03 suggests moderate variability in responses. The skewness and kurtosis values show that data distribution is symmetric and flatter than usual with a range from -0.50 to 0.06 and -0.84 to -0.18, respectively. This indicates that the construct has sufficient dispersion for determining relationships and retains adequate discriminatory power to distinguish itself from other constructs.

5.2.3.5 Innovation investments and process (IIP)

The descriptive analysis are as follows for the IIP variables: 3.07 – 3.65 for the mean, implying that respondents generally agree with the statements, but not strongly. The standard deviation of 0.89 – 1.11 indicates moderate variability. The skewness and kurtosis values range from -0.82 to -0.06 and -0.82 to 0.19, respectively, suggesting that the distributions are slightly left-skewed, meaning responses lean toward agreement.

5.2.3.6 Organisational learning capability (OLC)

The descriptive analyses are as follows for the OLC variables: 3.28 – 3.69 for the mean indicating that respondents generally hold positive perceptions. The standard deviation of 0.86 – 1.08 shows moderate variability. The skewness and kurtosis values range from -0.93 to -0.31 and -0.59 to 1.20, respectively showing that respondents are leaning towards higher agreement levels. Overall, the construct has sufficient dispersion for determining relationships and retains adequate discriminatory power suitable for further statistical analysis.

5.2.3.7 Summary of descriptive data analysis

Overall, the mean values across eight constructs ranged between 2.86-4.08 on a 5-point Likert scale, suggesting that respondents suggested neutral to high levels of perceptions on the constructs. ES, OS an OLC show the highest level of positive perception with mean of: 3.65-4.09; 3.24-3.72; and 3.28-3.69, respectively. On the other hand, FC, NI, and EC indicate neutral responses, i.e., 2.77-3.28; 2.85-3.24 and 2.97–3.14, respectively, and the responses on the remainder constructs, i.e., IIP, KAS and CL show somewhat agreement. Standard deviations across constructs fall between 0.86 and 1.19, suggesting moderate variability and sufficient dispersion around the mean. Skewness (asymmetry around the mean) and kurtosis (peaked shape around the mean) values show that the constructs retain adequate discriminatory power to distinguish themselves from other constructs; therefore, enabling further statistical analysis.

5.3 Measurement model (outer model) assessment

According to Aburumman et al. (2023), the measurement model (outer model) describes the relationship between a latent variable and its indicators or relationship between observable and underlying constructs. This ensures that the objective of the survey items is reached, and the survey instrument is valid and reliable. Therefore, the internal consistency reliability, i.e., Cronbach's alpha (CA) and composite reliability (CR); convergent validity and discriminant validity.

Table 9: Data validation to confirm the measurement model

	Construct	Alpha	CR	AVE	k
	<chr>	<dbl>	<dbl>	<dbl>	<int>
1	ES	0.781	0.852	0.535	5
2	OS	0.777	0.852	0.539	5
3	FC	0.754	0.835	0.46	6
4	CL	0.873	0.908	0.663	5
5	EC	0.893	0.922	0.703	5
6	NI	0.895	0.922	0.703	5
7	KAS	0.934	0.945	0.633	10
8	IIP	0.846	0.896	0.635	5
9	OLC	0.845	0.89	0.619	5

5.3.1 Internal consistency reliability

Cronbach's alpha and composite reliability are the most common methods for measuring internal consistency reliability. Cronbach's alpha provides an estimate of the reliability based on the intercorrelations of the observed item's variables, while composite reliability indicates "the level of reliability from 0 to 1 but is more scale-independent and less conservative" (Russo & Stol, 2021: 10). Generally, values between 0.70 and 0.95 for Cronbach's alpha (CA) and composite reliability (CR) are widely accepted (Aburumman et. al., 2023). The CA values ranged from 0.754 to 0.934 and CR values ranged from 0.873 and 0.945. As a result, the model of this study has internal consistency reliability.

5.3.2 Convergent Validity

Convergent validity refers to test whether “indicators developed to measure a particular construct are actually measuring that construct” (Aburumman et. al., 2023: 1200). Convergent validity was examined using Average Variance Extracted (AVE), which measures the proportion of variance explained by the construct relative to the variance due to measurement error. All constructs recorded AVE values above 0.50 demonstrate that the indicators shared enough variance in explaining their respective latent constructs. Therefore, the results confirm that the measurement model meets the minimum criteria for convergent validity.

In conclusion, reliability analysis confirmed that constructs were internally consistent, with Cronbach’s alpha and Composite Reliability values above 0.70. Convergent validity was supported, as all constructs achieved AVE values exceeding 0.50, except for Firm Competitiveness (0.46) which remained acceptable due to a high CR value (0.835). These results confirmed that the measurement model was reliable and valid for further structural analysis.

5.3.3 Discriminant Validity

To ensure that the constructs in this study are empirically distinct, discriminant validity was evaluated using three approaches: the Heterotrait–Monotrait ratio of correlations (HTMT), the Fornell–Larcker criterion and Fornell–Larcker matrix. These tests confirm that each latent construct measures a unique conceptual dimension rather than overlapping with related constructs, a major step given the conceptual proximity between variables such as communication, collaboration, and organisational learning.

5.3.3.1 HTMT

The Heterotrait–Monotrait (HTMT) ratios were used to assess discriminant validity among the constructs in this study. The HTMT approach compares the average correlations between indicators of different constructs (heterotrait) with those within the same construct (monotrait).
A value below 0.85 (strict) indicates strong discriminant validity, while values below 0.90 (liberal) remain acceptable when constructs are theoretically related.

Discriminant validity was supported, as all HTMT ratios (Table 10) were below the 0.90 criterion, with most well under the stricter 0.85 threshold. However, the two construct pairs, Communication Loop and Employee Collaboration (HTMT = 0.866) and Knowledge and Asset Sharing with Innovation Investment and Process (HTMT = 0.868) slightly exceeded the stricter 0.85 threshold but remain within the acceptable 0.90 criterion. These minor deviations are theoretically justifiable given the conceptual proximity of the constructs. Complementary diagnostics, i.e., Fornell–Larcker Criterion (Figure 11 below) further corroborated discriminant validity.

Table 10: HTMT Ratios

Construct_1	Construct_2	HTMT	Pass_0_85	Pass_0_90
ES	OS	0.576	PASS	PASS
ES	FC	0.311	PASS	PASS
ES	CL	0.392	PASS	PASS
ES	EC	0.346	PASS	PASS
ES	NI	0.338	PASS	PASS
ES	KAS	0.393	PASS	PASS
ES	IIP	0.391	PASS	PASS
ES	OLC	0.373	PASS	PASS
OS	FC	0.534	PASS	PASS
OS	CL	0.778	PASS	PASS
OS	EC	0.589	PASS	PASS
OS	NI	0.56	PASS	PASS
OS	KAS	0.664	PASS	PASS
OS	IIP	0.65	PASS	PASS
OS	OLC	0.599	PASS	PASS
FC	CL	0.637	PASS	PASS
FC	EC	0.601	PASS	PASS
FC	NI	0.322	PASS	PASS
FC	KAS	0.367	PASS	PASS
FC	IIP	0.496	PASS	PASS
FC	OLC	0.368	PASS	PASS
CL	EC	0.866	FLAG	PASS
CL	NI	0.69	PASS	PASS

CL	KAS	0.777	PASS	PASS
CL	IIP	0.748	PASS	PASS
CL	OLC	0.636	PASS	PASS
EC	NI	0.548	PASS	PASS
EC	KAS	0.645	PASS	PASS
EC	IIP	0.607	PASS	PASS
EC	OLC	0.645	PASS	PASS
NI	KAS	0.815	PASS	PASS
NI	IIP	0.772	PASS	PASS
NI	OLC	0.55	PASS	PASS
KAS	IIP	0.868	FLAG	PASS
KAS	OLC	0.69	PASS	PASS
IIP	OLC	0.765	PASS	PASS

5.3.3.2 Fornell–Larcker Criterion

The Fornell–Larcker criterion (Table 11) compares the square root of the Average Variance Extracted (√AVE) for each construct with its correlations with other constructs. Fornell–Larcker's criterion was satisfied for all constructs, as the square roots of the Average Variance Extracted (√AVE) on the diagonal exceeded the corresponding inter-construct correlations. For example, Dynamic Sensing Capabilities (√AVE = 0.73) exhibited stronger association with its own indicators than with any other construct (r = 0.20-0.44), and Inside-In Innovation sub-constructs such as Collaboration Loop (√AVE = 0.81) and Employee Collaboration (√AVE = 0.84) showed analogous patterns. Across the measurement model, diagonal √AVE values ranged from 0.676 to 0.839 and consistently surpassed off-diagonal correlations, confirming discriminant validity. Notably, the lower bound of √AVE suggests that at least one construct may exhibit marginal convergent validity (AVE < 0.50), which is acceptable when composite reliability is adequate, but merits acknowledgement and, if necessary, item refinement. Together with the HTMT results, these findings support the empirical distinctiveness of the latent constructs.

Table 11:Fornell–Larcker Criterion

Construct_1	Construct_2	Latent_r	sqrtAVE_1	sqrtAVE_2	FL_Pass_1	FL_Pass_2
CL	EC	0.760809	0.812628	0.838542	PASS	PASS
CL	ES	0.326723	0.812628	0.731598	PASS	PASS
CL	FC	0.52027	0.812628	0.676229	PASS	PASS
CL	IIP	0.646572	0.812628	0.794662	PASS	PASS
CL	KAS	0.701663	0.812628	0.794203	PASS	PASS
CL	NI	0.609147	0.812628	0.838165	PASS	PASS
CL	OLC	0.545223	0.812628	0.785517	PASS	PASS
CL	OS	0.645362	0.812628	0.733964	PASS	PASS

EC	CL	0.760809	0.838542	0.812628	PASS	PASS
EC	ES	0.292481	0.838542	0.731598	PASS	PASS
EC	FC	0.507699	0.838542	0.676229	PASS	PASS
EC	IIP	0.52812	0.838542	0.794662	PASS	PASS
EC	KAS	0.587152	0.838542	0.794203	PASS	PASS
EC	NI	0.484331	0.838542	0.838165	PASS	PASS
EC	OLC	0.564844	0.838542	0.785517	PASS	PASS
EC	OS	0.490352	0.838542	0.733964	PASS	PASS
ES	CL	0.326723	0.731598	0.812628	PASS	PASS
ES	EC	0.292481	0.731598	0.838542	PASS	PASS
ES	FC	0.202949	0.731598	0.676229	PASS	PASS
ES	IIP	0.321313	0.731598	0.794662	PASS	PASS
ES	KAS	0.335626	0.731598	0.794203	PASS	PASS
ES	NI	0.285131	0.731598	0.838165	PASS	PASS
ES	OLC	0.30443	0.731598	0.785517	PASS	PASS
ES	OS	0.442805	0.731598	0.733964	PASS	PASS
FC	CL	0.52027	0.676229	0.812628	PASS	PASS
FC	EC	0.507699	0.676229	0.838542	PASS	PASS
FC	ES	0.202949	0.676229	0.731598	PASS	PASS
FC	IIP	0.39673	0.676229	0.794662	PASS	PASS
FC	KAS	0.298473	0.676229	0.794203	PASS	PASS
FC	NI	0.23261	0.676229	0.838165	PASS	PASS
FC	OLC	0.267408	0.676229	0.785517	PASS	PASS
FC	OS	0.413166	0.676229	0.733964	PASS	PASS
IIP	CL	0.646572	0.794662	0.812628	PASS	PASS
IIP	EC	0.52812	0.794662	0.838542	PASS	PASS
IIP	ES	0.321313	0.794662	0.731598	PASS	PASS
IIP	FC	0.39673	0.794662	0.676229	PASS	PASS
IIP	KAS	0.772843	0.794662	0.794203	PASS	PASS
IIP	NI	0.671678	0.794662	0.838165	PASS	PASS
IIP	OLC	0.649962	0.794662	0.785517	PASS	PASS
IIP	OS	0.530022	0.794662	0.733964	PASS	PASS
KAS	CL	0.701663	0.794203	0.812628	PASS	PASS
KAS	EC	0.587152	0.794203	0.838542	PASS	PASS
KAS	ES	0.335626	0.794203	0.731598	PASS	PASS
KAS	FC	0.298473	0.794203	0.676229	PASS	PASS
KAS	IIP	0.772843	0.794203	0.794662	PASS	PASS
KAS	NI	0.74214	0.794203	0.838165	PASS	PASS
KAS	OLC	0.611594	0.794203	0.785517	PASS	PASS
KAS	OS	0.567433	0.794203	0.733964	PASS	PASS
NI	CL	0.609147	0.838165	0.812628	PASS	PASS
NI	EC	0.484331	0.838165	0.838542	PASS	PASS
NI	ES	0.285131	0.838165	0.731598	PASS	PASS
NI	FC	0.23261	0.838165	0.676229	PASS	PASS
NI	IIP	0.671678	0.838165	0.794662	PASS	PASS
NI	KAS	0.74214	0.838165	0.794203	PASS	PASS
NI	OLC	0.480717	0.838165	0.785517	PASS	PASS
NI	OS	0.463365	0.838165	0.733964	PASS	PASS

OLC	CL	0.545223	0.785517	0.812628	PASS	PASS
OLC	EC	0.564844	0.785517	0.838542	PASS	PASS
OLC	ES	0.30443	0.785517	0.731598	PASS	PASS
OLC	FC	0.267408	0.785517	0.676229	PASS	PASS
OLC	IIP	0.649962	0.785517	0.794662	PASS	PASS
OLC	KAS	0.611594	0.785517	0.794203	PASS	PASS
OLC	NI	0.480717	0.785517	0.838165	PASS	PASS
OLC	OS	0.475417	0.785517	0.733964	PASS	PASS
OS	CL	0.645362	0.733964	0.812628	PASS	PASS
OS	EC	0.490352	0.733964	0.838542	PASS	PASS
OS	ES	0.442805	0.733964	0.731598	PASS	PASS
OS	FC	0.413166	0.733964	0.676229	PASS	PASS
OS	IIP	0.530022	0.733964	0.794662	PASS	PASS
OS	KAS	0.567433	0.733964	0.794203	PASS	PASS
OS	NI	0.463365	0.733964	0.838165	PASS	PASS
OS	OLC	0.475417	0.733964	0.785517	PASS	PASS

5.3.3.3 Fornell-Larcker Matrix

The Fornell–Larcker Correlation Matrix (Table 12) provides further evidence of discriminant validity by comparing each construct's square root of the Average Variance Extracted (√ AVE) with its correlations with other constructs. In this study, all constructs satisfied the criterion, each √ AVE value (ranging from 0.68 to 0.84) was greater than the corresponding inter-construct correlations (ranging from 0.20 to 0.76). This confirms that each construct shares more variance with its own indicators than with other constructs, demonstrating that the latent variables are empirically distinct.

Table 12: Fornell-Larcker Correlation Matrix

Construct	ES	OS	FC	CL	EC	NI	KAS	IIP	OLC
ES	0.731598	0.442805	0.202949	0.326723	0.292481	0.285131	0.335626	0.321313	0.30443
OS	0.442805	0.733964	0.413166	0.645362	0.490352	0.463365	0.567433	0.530022	0.475417
FC	0.202949	0.413166	0.676229	0.52027	0.507699	0.23261	0.298473	0.39673	0.267408
CL	0.326723	0.645362	0.52027	0.812628	0.760809	0.609147	0.701663	0.646572	0.545223
EC	0.292481	0.490352	0.507699	0.760809	0.838542	0.484331	0.587152	0.52812	0.564844
NI	0.285131	0.463365	0.23261	0.609147	0.484331	0.838165	0.74214	0.671678	0.480717
KAS	0.335626	0.567433	0.298473	0.701663	0.587152	0.74214	0.794203	0.772843	0.611594
IIP	0.321313	0.530022	0.39673	0.646572	0.52812	0.671678	0.772843	0.794662	0.649962
OLC	0.30443	0.475417	0.267408	0.545223	0.564844	0.480717	0.611594	0.649962	0.785517

These findings strengthen confidence in the measurement model and show that the constructs, Dynamic Sensing Capabilities, Inside-In Innovation, and Firm

Competitiveness capture unique conceptual domains. This means that the observed relationships in the structural model are not inflated by redundancy or conceptual overlap between constructs, supporting the integrity and reliability of subsequent hypothesis testing.

5.4 Structural Model Evaluation and Hypothesis Testing

5.4.1 Coefficient of determination (R^2)

According to Russo and Stol (2023), "the coefficient of determination explained variance, or R^2 value is an essential measure in R-package cSEM, since it measures the model's explanatory power. It measures the proportion of variance explained by each endogenous construct" (p16). In the structural model, values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak for R^2 (Aburumman et al., 2023).

Table 12: Coefficient of determination (R^2)

	Construct	R^2	Interpretation
1	III	0.425	Predictive relevance
2	FC	0.323	Predictive relevance

The results as shown in Table 19 indicate that the model explains a moderate proportion of variance in both Inside-In Innovation (R^2 = 0.425) and Firm Competitiveness (R^2 = 0.323). This means that Dynamic Sensing Capabilities account for around 42.5% of the differences in innovation performance across firms, while the combined effects of sensing and innovation explain roughly 32.3% of competitiveness outcomes. In practical terms, the model demonstrates moderate explanatory power, confirming that these constructs meaningfully contribute to how firms sense opportunities, Inside-In Innovation, and sustain competitiveness.

5.4.2 Cross-validated redundancy (Q^2)

Table 13: Cross-validated redundancy (Q^2)

	Construct	Q2	Interpretation
1	III	0.343	Predictive relevance
2	FC	0.156	Predictive relevance

To assess predictive relevance in reflective structural model, Stone-Geisser's (Q^2) is calculated (Russo & Stol, 2023). Q^2 values greater than zero are considered meaningful (Aburumman et al., 2023). However, Russo and Stol (2023) provide the following value ranges, "small (higher than 0), medium (larger than 0.25), or large (greater than 0.50)"

(p. 16). The 10-fold cross-validated redundancy values (Q^2) were positive for both Inside-In Innovation ($Q^2 = 0.343$) and Firm Competitiveness ($Q^2 = 0.156$), demonstrating meaningful out-of-sample predictive relevance. Therefore, the relatively higher Q^2 for Inside-In Innovation suggests that the model predicts this construct particularly well, while the positive Q^2 for firm competitiveness confirms adequate predictive relevance at the outcome level. Collectively, these findings affirm that the structural model has substantial predictive capability and external validity.

5.4.3 Effect sizes (f^2)

The effect size (f^2) measures if the exogenous construct has a huge impact on the endogenous one (Russo & Stol, 2023). Indicative thresholds for the structural model are: value below 0.02 represents negligible or no effect, 0.02–0.15 is considered a small effect size, 0.15-0.35 a medium sized effect, and above 0.35 a large effect size (Aburumman et al., 2023).

Table 14: Effect Sizes

	Path	f^2	Magnitude
1	DSC → III	0.572	Large
2	III → FC	0.112	Small
3	DSC → FC	0.017	negligible

The effect sizes of DSC → III was considered large (i.e., 0.572); III → FC was considered small; and lastly, DSC → FC was considered negligible. These results show that Dynamic Sensing Capabilities have a strong and meaningful influence on Inside-In Innovation (large effect), confirming that firms with better sensing abilities are significantly more likely to innovate. The small effect of Inside-In Innovation on Firm Competitiveness indicates that while innovation contributes to competitiveness, it "probably" does so alongside other external factors not captured in the model. The negligible direct effect of Dynamic Sensing Capabilities on Firm Competitiveness reinforces the mediation finding that sensing only improves competitiveness when mediated by Inside-In Innovation. Overall, these results highlight that the real value of sensing capabilities lies in how effectively they drive Inside-In Innovation within the firm.

Collectively, these results highlight that the dominant pathway from sensing to competitiveness is indirect, operating through Inside-In Innovation. This supports the central proposition of dynamic capability theory, that organisational sensing becomes valuable only when internal innovation mechanisms convert environmental awareness into tangible firm-level performance advantages.

5.4.4 Path coefficients (hypotheses testing)

This section presents the results of the structural model analysis used to test the proposed hypotheses. The analysis looked at how the main variables in the study relate to each other, i.e., Dynamic Sensing Capabilities (DSC), Inside-In Innovation (III), and Firm Competitiveness (FC).

The model examined the direct and indirect effects among Dynamic Sensing Capabilities (DSC), Inside-In Innovation (III), and Firm Competitiveness (FC). DSC, a second-order construct comprising of Environmental Scanning and Opportunity Selection, was hypothesised to influence FC both directly and indirectly through Inside-In Innovation (III). Inside-In Innovation (III) construct encompassed communication, collaboration, idea generation, knowledge sharing, implementation, and organisational learning.

Bootstrapped results (5,000 resamples) provided estimates of path coefficients, standard errors, t-values, p-values, and 95% confidence intervals. The model explained 42.5% of the variance in Inside-In Innovation and 32.3% in Firm Competitiveness, supporting the mediating role of internal innovation in translating. sensing capabilities into competitiveness.

Table 15: Detailed path Coefficients and hypothesis testing results

Detailed path coefficients						
Path	Estimate β	Standard Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)
DSC → III	0.652	0.055	11.88	<0.001	0.544	0.759
DSC → FC	0.087	0.129	0.67	0.509	-0.167	0.340
III → FC	0.508	0.122	4.08	<0.001	0.269	0.748
R^2 (III) = 0.425; R^2 (FC) = 0.323						
Hypothesis testing results						
Hypothesis		Relationship		t	p	Supported
H_1		DSC → FC	0.09	0.66	0.509	Not supported
H_2		DSC → III	0.65	11.67	<0.001	Supported
H_3		III → FC	0.51	4.08	<0.001	Supported
H_4		DSC → III → FC (Mediation)	-	-	-	Supported (full mediation)

Two steps are required to examine the path coefficients (hypotheses testing), the p-value is required to be <0.05 and secondly, the confidence interval must be zero and not cross. If these two steps are met, then the path or hypothesis is considered statistically supported

5.4.5 Hypothesis 1 (H_1) analysis excluding control variables

It was hypothesized that Dynamic Sensing Capabilities (DSC) positively influence Firm Competitiveness (FC). That is, H_1: DSC → FC. The results of H_1 analysis are presented without inclusion of the control variables below.

For the relationship to be considered statistically supported, the p-value is required to be <0.05 and secondly, the confidence interval must be zero and not cross. However, $p = 0.509$, CI (lower) = -0.167 and CI (upper) = 0.340. Therefore, the direct relationship between DSC and FC is considered not statistically supported.

5.4.6 Hypothesis 2 (H_2) analysis excluding control variables

It was hypothesised that Dynamic Sensing Capabilities (DSC) positively influence Inside-In Innovation (III). That is, H_2: DSC → III. The results of H_2 analysis are presented without inclusion of the control variables below.

For the relationship to be considered statistically supported, the p-value is required to be <0.05 and secondly the confidence interval must be zero and not cross. The test outcomes show that, $p < 0.001$, CI (lower) = 0.544 and CI (upper) = 0.759. Therefore, the direct relationship between DSC and III is considered statistically supported.

5.4.7 Hypothesis 3 (H_3) analysis excluding control variables

It was hypothesized that Inside-In Innovation (III) positively influences Firm Competitiveness (FC). That is, H_3: III → FC. The results of H_3 analysis are presented below without inclusion of the control variables.

For the relationship to be considered statistically supported, the p-value is required to be <0.05 and secondly, the confidence interval must be zero and not cross. The test outcomes show that, $p < 0.001$, CI (lower) = 0.269 and CI (upper) = 0.748. Therefore, the direct relationship between III and FC is considered statistically supported.

5.4.8 Hypothesis 4 (H4) analysis excluding control variables

It was hypothesised that Inside-In Innovation (III) mediates the relationship between Dynamic Sensing Capabilities (DSC) and Firm Competitiveness (FC). That is, H_4: Mediation (DSC → III → FC). The results of H_4 analysis are presented below without inclusion of the control variables.

Indirect path (DSC → III → FC) was considered statistically supported while the direct path (DSC → FC) was considered not statistically supported, therefore, this indicates full mediation.

5.4.9 Model Robustness and Outlier Sensitivity

To ensure robustness, an outlier sensitivity analysis was conducted using the 1.5 × IQR rule across all first-order indicators. The R script identified 35 of 107 cases as potential outliers across at least one indicator. These 35 outlier cases that manifested as statistical outliers were because of incomplete survey questions, resulting in missing data in the model and this has potential to raise concerns about sample integrity, measurement invariance, or introduce bias according to scholarly literature (Li & Lomax, 2017). A case wise sensitivity test was done on R package cSEM including the full data set (n=107) and re-estimated on a cleaned version of the data excluding the flagged cases (n=72). The results were compared with the full sample in Table 16.

Table 16: Sensitivity analysis of the structural model

Path	Full data β	Cleaned data β	Delta β	Significance (both)
DSC → III	0.652	0.664	+0.012	Significant (p<0.001)
DSC → FC	0.087	-0.007	-0.094	Significant (p<0.001)
III → FC	0.508	0.593	+0.094	Not significant
Construct		R^2 (full data)	R^2 (Cleaned data)	Delta R^2
Inside-In Innovation (III)		0.425	0.441	+0.016
Firm Competitiveness (FC)		0.323	0.346	+0.023

The results showed only marginal differences: maximum $|\Delta\beta| = 0.094$ and $|\Delta R^2| = 0.023$. This confirms that the model results are stable and not unduly influenced by extreme responses. Therefore, the full dataset was retained for interpretation and reporting. The maximum absolute change observed across standardised path coefficients was 0.094 and across R^2 values 0.023 which is well within the range that is considered statistically stable. The consistency of path coefficients model fit statistics when using full data set and cleaned data version confirms robustness of the model and mitigates any concerns relating to incomplete surveys on the model outcomes.

5.4.10 Hypotheses testing including control variables

To test whether control variables (such as gender, education, and experience) could have influenced the relationships observed in our main R package cSEM model, a robustness check was conducted by extending the structural model to include demographic variables as control variables.

5.4.6.1 Logic

Control variables were added as single-indicator latent constructs (each measured by one standardized variable: Gender_z, Edu_z, Exp_z). These controls were added as predictors of both Inside-In Innovation (III) and Firm Competitiveness (FC). Company size was excluded due to insufficient data variation (all missing/constant responses). The controls were entered as single-indicator constructs standardized as z-scores. An objective was to check whether including controls changes the path coefficients (β) or R^2 values meaningfully. If not, it means the main relationships (H1–H4) are stable and not driven by demographic bias.

5.4.6.2 Rationale for Using R package cSEM for Control Variables

The same R package cSEM framework was retained due to the following:

- It allows simultaneous estimation of multiple endogenous constructs.
- It handles small samples well (n = 104).
- It is robust to moderate non-normality in data.
- It supports inclusion of single-indicator constructs (controls) easily.

5.4.6.3 Model outcomes

Model outcomes can be summarised as follows (Table 17):

- The effect of DSC on III remained strong and significant ($p<0.001$) even after inclusion of demographics.
- The direct effect of DSC on FC remained weak and statistically insignificant.
- The effect of III on FC is robust and significant ($p<0.001$).
- Maximum absolute change (Delta β):0.039, indicating minimal impact of controls on the structural relationships.

Table 17: Structural path comparison

Path	Base estimate β	With controls β	Delta β	t-base	t-control
DSC → III	0.652	0.613	-0.039	11.88	7.95
DSC → FC	0.087	0.094	+0.007	0.67	0.74

III → FC	0.508	0.509	0.00	4.16	4.22

R^2 results can be summarised as follows (see Table 18):

- Minor 1.4% improvement in explanatory power, negligible practical effect
- The addition of controls improved R^2 by ~3.7% showing limited incremental variance explained.

Table 18: R^2 comparison

Construct	R^2 (Base)	R^2 (With controls)	Delta R^2
III	0.425	0.439	+0.014
FC	0.323	0.360	+0.037

Therefore, inclusion of controls led to only marginal changes in the structural paths (maximum $|\Delta\beta| = 0.039$) and small increases in R^2 ($\Delta R^2 \leq 0.037$). The main relationships between Dynamic Sensing Capabilities, Inside-In Innovation, and Firm Competitiveness remained significant and directionally consistent.

5.5 Conclusion

The results of the study were presented and analysed including the demographic analysis, descriptive statistics, data validation, SEM analysis, and sensitivity analysis. The demographics confirmed that respondents represented the targeted population. The descriptive data included measures of central tendency, dispersion, peaked shape, and asymmetry around the mean and the data confirmed that the constructs displayed adequate discriminatory power to distinguish itself from others, enabling further statistical analysis.

Internal consistency reliability and validity of measurement model (outer model) were measured, and results will be discussed in the next chapter. Lastly, structural (outer) model displayed adequate explanatory power and the interpretation of the structural model, focusing on the model explanatory power and hypotheses testing are discussed in detail in Chapter 6.

CHAPTER 6: DISCUSSION

The aim of the study was to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning).

The study commenced with an introduction in Chapter 1, providing motivation for research. The foundation of the research done by interrogating the latest literature on the research constructs and their relationships in Chapter 2. Emerging hypotheses and conceptual model were developed in Chapter 3. Research methodology and presentation of study results were presented in Chapter 4 and 5, respectively.

Building on the empirical results presented in Chapter 5, this chapter contextualises the demographic data of the respondents; discusses the descriptive statistics; assesses the measurement model (outer model) and the structural model (inner model); and focuses on the model’s explanatory power and hypotheses testing.

6.1 Discussion on demographics

Summary of the demographics is as follows:

Table 19: Summary of demographic data

Gender	Number of responses	Percentage (%)
Female	45	43%
Male	58	56%
Prefer not to say	1	1%
Age, in years	Number of responses	Percentage (%)
<18	0	0
18-24	0	0
25-34	8	7.7
35-44	46	44
45-54	38	37
>55	12	12
Education levels	Number of responses	Percentage (%)
No formal education	0	0
Matric or equivalent	0	0
Diploma	1	1
Bachelor’s degree	7	7
Honours	28	27
Master’s degree	59	57
Doctorate or higher	9	8.7
Work experience, in years	Number of responses	Percentage (%)
0-4	2	2
5-9	5	5
10-15	20	19
16-20	30	29
>20	47	45
Work titles/ roles	Number of responses	Percentage (%)
Manager	30	29
Senior Management	30	29
Executive	15	14
Other	29	28
Work titles/ roles	Number of responses	Percentage (%)
Technical	30	29
Strategic	62	60
Other	12	12
Company size	Number of responses	Percentage (%)
0-500	19	18
501-5000	22	21
>5000	63	61
Company sector	Number of responses	Percentage (%)
Energy	88	85%
Other	15	15%
Energy value chain play	Number of responses	Percentage (%)
Upstream	33	32
Midstream	31	30
Downstream	40	38

The respondents’ gender distribution deviates from the energy sector representation. However, according to Quezada et al. (2025), though female and male dynamic capabilities are similar, females tend to demonstrate more sensing capabilities in comparison to their counterparts. In addition, Roberson et al. (2017) purport that employee heterogeneity in age, work experience, gender, and education levels enhances innovation within the firm. However, it is notable that though both genders are reasonably represented, our respondents are concentrated in the ages in the age category 35-54 with no representation in the 18-24 years old; 93% and above had over 10 years’ experience, 72% being in management roles and executive roles focusing on strategic issues and, 93% of the respondents having honours degrees and higher. These insights are critical as Arnt et al. (2022) argue that age, gender, and education as control variables are crucial for the sensing capabilities scholarly literature.

Moreover, Fenech et al. (2022) postulate that educational background and prior work experience shape how management or leaders deploy sensing capabilities and internally reconfigure resources to exploit emerging opportunities. Arndt et al. (2022) argue that larger firms tend to have resources to build sensing capabilities which is aligned with 61% of the respondents being employed by companies with more than 5000 employees. However, the scholars argue that such firms are confronted with bureaucracy which slows the required reconfiguration, and of course, the opposite is true for the smaller firms, i.e., 39%.

6.2 Discussion on descriptive analysis of research constructs

6.2.1 Dynamic sensing capabilities (DSC)

Scholarly literature conceptualises sensing capabilities as systematic environmental scanning whereby detection and systemically collecting data from various sources externally or internally, with an objective of enabling analysis and dissemination of insights (Teece, 2020; Teece et al., 2020). The empirical evidence strongly supports this theoretical position, as respondents affirm that on a regular basis, local and international market trends are assessed; technology developments are followed; and customers' experiences and emerging needs are assessed. Furthermore, enough time is spared to observe and evaluate business environment, and environmental changes seem to be noticed early. Furthermore, Arndt et al. (2022) argues that larger firms tend to have resources to build sensing capabilities and this have been corroborated by the demographic data as the majority of the respondents work for firms with more than 5000 employees.

Moreover, scholarly literature postulate that construal management is inclined to embed sensing capabilities and recognise the opportunity set and have data gathering and sharing systematic approach, and this is supported by the respondents' strongly agreeing to environmental scanning. The respondents also agreed that there is orientation towards high finance value projects even if the projects are risky. Furthermore, leadership champions sponsorship for new opportunities and leadership encourages diversity of thoughts to ensure richness of the opportunity funnel. These empirical findings support theoretical perspective that data insights gathered during environmental scanning include customer needs, competitors, and technology trends to identify opportunities and threats from landscape developments and it is used for developing tacit knowledge and experiential learning (Harvey, 2022; Zabel, 2023; khan et al., 2020). In addition, respondents agree that 'bold strokes are taken when searching for new opportunities, and new and original ideas are encouraged in the organisation', which aligns with Bogers et al. (2019) that dynamic sensing enables capturing of new information and knowledge which is critical for identification of emerging opportunities (Bogers et al., 2019).

These findings reinforce the argument that sensing capabilities, underpinned by leadership commitment and resource availability, are fundamental to fostering innovation.

6.2.1 Firm Competitiveness (FC)

Suprihono et al. (2022) argue that cost leadership enable firm competitiveness, a view supported by respondents who agree that costs have been managed and contained over the past three years. Academic discourse further posits that competitiveness can be accessed through indicators such as introduction and evaluations of new products or services and sales volumes (Mikalef & Pateli, 2017; Pundziene et al., 2022). The findings partially align with this perspective. The respondents indicate that sales have partially grown over the past three years and their enterprise's new products or services received better evaluations than the new products and services of our competitors.

However, evidence also revealed areas of divergence. The respondents partially disagree that sales of their enterprise have risen faster than sales of their competitors; their enterprise creates more products/services per year than their competitors and market share has improved over the past three years. This aligns with Arokodare et al.'s (2020) argument that firms struggle to maintain their performance and market share due to rapidly changing context. These findings suggest that cost containment and product evaluations contribute to competitiveness but not guarantee superior performance.

In conclusion, although dynamic sensing is applied within the energy industry, there appears to be a disconnect between its application and the ability to translate it into tangible competitive advantage. Supporting this view, Bayighomog Likoum et al. (2020) emphasize that the integration of external information with internal resources and competencies is central to the dynamic capabilities' framework. Without such integration, efforts to maintain competitiveness may remain fragmented and insufficient.

6.2.2 Inside-In Innovation

6.2.2.1 Communication loop

Theoretical perspectives suggest that internal innovation decisions are primarily shaped by high-construal managers (Bornay-Barrachina et al., 2025; Harvey, 2022; Harvey, 2025). The results indicate concurrence to this theoretical perspective. The respondents corroborate this view as respondents agree that leadership champions sponsorship for new opportunities and demonstrates culture of innovation, i.e., “tone at the top”. This alignment between theory and practice shows the critical role of leadership in enabling innovation within firms.

Furthermore, Machado et al. (2025) argue that collaborative and transparent work environments supported by internal communication foster innovative workforce, and the findings partially support this claim, indicating that communication culture exist to some extent. In addition, the findings indicates that bottom-up communication on innovative ideas is enabled through supporting tools and systems and the frequency of communication somewhat supports innovative culture. However, respondents neutral regarding the visibility and accessibility of innovation progress dashboards and other communication tools across the organisation. This neutrality suggests that while mechanisms for idea-sharing are present, transparency in tracking innovation progress may be insufficient, potentially limiting the effectiveness of communication in sustaining innovation momentum.

These findings suggest that while leadership and cultural factors promote innovation, emergent gaps in communication visibility diminishes full realisation of collaborative innovation.

6.2.2.2 Employee collaboration

Knox and Marin-Cadavid (2023) argue that employee engagement is critical in unlocking innovation in firms, and it requires freeing-up extra resources, change in the organisational structures, and decision-making power. In addition, Van der Voet and Steijn (2021) suggests that employee collaborations unlock innovation potential through existing expertise, connections, financial resources, and knowledge within an organisation. In addition, the scholars suggest that decoupling organisation units reduces innovation participation and restricts resources. The evidence from the findings supports this view. The respondents agree that coordination among business units and project teams are timely and efficient, and intra-organisational collaboration is across all levels.

Furthermore, performance review process is perceived to encourage collaboration across teams.

However, Van der Voet and Steijn (2021) caution that visionary leadership is required to enable team cohesion, a concern highlighted in the findings, which reveal emerging gaps in cohesion attributed to restrictive reward and recognition policies and the absence of innovation platform ecosystems, both of which stifle collaborative potential.

6.2.2.3 New ideas

Valtonen et al. (2023) claim that new ideas required to enable Inside-In Innovation depends on individual level factors such as expertise, social currency and motivation levels. The practical evidence partially supports this theoretical evidence. The findings indicate that respondents partially agree that on a regular basis, new ideas are logged onto the innovation system. Furthermore, the official internal innovation networks established to encourage new ideas creation and ideation platforms are accessible to teams across the organisation. These mechanisms suggest an organisational commitment to facilitating idea generation.

However, Valtonen et al. (2023) further caution that idea generation on its own is not sufficient and it needs to translate into implementation through resource allocation and sponsorships. The findings deviate from this perspective, revealing significant gaps in the innovation cycle. Respondents indicate absence of innovation events designed to inspire idea generation across organisation; and note that not even a single idea per annum is incubated through the innovation cycle.

Though structural provisions for idea logging and networking exist, the disconnect between ideation and implementation shows weakness in the mechanism leading to failure in producing tangible innovation outcomes. Failure to bridge this gap will lead to benefits of individual level creativity not yielding competitiveness.

6.2.2.4 Knowledge and asset sharing

Knowledge management infrastructure and processes are argued to be critical in enabling Inside-Inn Innovation and it is driven by the organisational culture and leadership (Ting et al., 2023). Evidence from the findings supports this theoretical position, indicating that energy firms conduct knowledge sharing sessions on regular basis on latest innovation developments and maintain knowledge centred culture in the organisation through accessible resources such as databases and newsletters. These practices suggest that the organisation prioritises systematic dissemination of information to foster innovation.

However, this perspective is contested by Yeboah (2023) who argues that such sessions often fail to deliver meaningful outcomes unless knowledge-sharing processes are strategically aligned with business objectives and resource allocation. This critique underscores the risk of treating knowledge management as a procedural formality rather than a value-driven activity.

Similarly, while respondents agree that assets are well maintained and are made available for innovative projects, including those at pilot phase and teams across the organisation also have access to these assets, this approach is not without limitations. Stojcic et al. (2025) caution that excessive reliance on intra-group resources, such as shared assets and employee mobility, can lead to a competency trap, ultimately constraining innovation and diminishing overall firm performance.

These arguments reveal a tension between the perceived benefits of knowledge and asset sharing and the potential pitfalls of misalignment and over-dependence.

6.4.4.2.6 Inside-In Innovation (Innovation investments and process)

Smith (2025) posits that innovation investment generates multiplier effect on firm competitiveness, a claim supported by the research findings which reveal that energy firms allocate annual budgets for innovation activities and have business and intelligence and analytics capabilities.

However, Zamaar et al. (2023) cautions that many firms lack adequate supporting tools and systems to enable the innovation process, thus creating decision making risks. This indicates that capital investments alone are insufficient without complementary technological and governance infrastructure. The results deviate from this assertion. The respondents indicate that existing processes and decision-making tools support each stage of innovation. Furthermore, there is clarity on when to proceed with innovative product/ service development, when to cut it, and when to increase or decrease investment. Lastly, existing innovation project management tools support to achieve satisfactory innovation speed, return of investment and outcomes.

The practical evidence highlights divergence from theoretical perspective that purport deficiencies as barriers to innovation. However, the energy firms have decision-making frameworks and project management tools to reduce such risks. This suggests that success of innovation investments hinges not only on capital allocation but integration of resources and processes to ensure strategic clarity.

6.2.2.5 Organisational learning

Pedraja-Rejas et al. (2025) purport that dynamic sensing capabilities enable organisational learning holistically as an integrated practice that is anchored on continuous improvement and fosters innovation. Complimenting this view, Efendi et al. (2020) argue that learning capability determines firm competitiveness. This theoretical perspective is supported by the practical evidence. The findings indicate that employees are proficient in project management, rotation or secondment opportunities, bottom-up learning, team learning and unlearning encouraged, and learning capabilities embedded across the organizations.

These findings confirm that learning capabilities are embedded throughout the organisation, reinforcing the argument that dynamic sensing and learning are interdependent drivers of innovation and competitiveness.

6.3 Measurement model (Outer model) Assessment

Internal consistency reliability of measurement (outer) model was measured using Cronbach’s alpha (CA) and composite reliability (CR) was found to be within acceptable limits of 0-1 and 0.70-0.95, respectively, aligned with theory (Aburumman et. al., 2023). Data validation was tested using convergent validity and discriminant validity measures to determine distinctiveness of each construct in the research model. Convergent validity was established using average variance extracted (AVE) which was above 0.50 for all constructs except for firm competitiveness (0.46), which means that construct explains less than half of the variance in its indicators. However, composite reliability (CR) for firm competitiveness was found to be 0.835 which suggests strong internal consistency reliability. This suggests that firm competitiveness measures are moderate but numerous improving CR while lowering AVE. Though this limitation is noted, the construct was kept in the model due to high CR (Fornell & Larcker, 1981).

Discriminant validity was evaluated using three approaches: the Heterotrait–Monotrait ratio of correlations (HTMT), the Fornell–Larcker criterion and Fornell–Larcker matrix. Fornell–Larcker Criterion and Fornell–Larcker matrix suggest that observed relationships of latent constructs in the measurement outer model are theoretically justifiable and not inflated by redundancy, i.e., supports the integrity and reliability of the measurement instrument and enable structural relationships testing. However, Ab Hamid et al. (2017) contend that the Fornell–Larcker criterion and its associated matrix exhibit insufficient sensitivity in assessing discriminant validity. In contrast, they advocate for the Heterotrait–Monotrait (HTMT) ratio as a superior approach, although conclusive empirical validation of this method remains forthcoming. The results of HTMT indicate that Communication Loop and Employee Collaboration (HTMT = 0.866) and Knowledge and Asset Sharing with Innovation Investment and Process (HTMT = 0.868) latent variables though lower than 0.90, deviated from the threshold (0.85) signalling potential multicollinearity issues due to the conceptual proximity of the constructs.

6.4 Structural Model Evaluation and Hypothesis Testing

Table 20: Hypotheses testing results summary

Detailed path coefficients (without controls)						
Path	Estimate β	Standard Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)
DSC → III	0.652	0.055	11.88	<0.001	0.544	0.759
DSC → FC	0.087	0.129	0.67	0.509	-0.167	0.340
III → FC	0.508	0.122	4.08	<0.001	0.269	0.748
R^2 (III) = 0.425; R^2 (FC) = 0.323		Q^2 (II) = 0.343; Q^2 (FC) = 0.156		f^2(DSC → FC) = 0.572; f^2 (III → FC) = 0.112; f^2 (DSC → III) = 0.017		
Hypothesis testing results (with controls)						
Hypothesis		Relationship	β	t	p	Supported
H_1		DSC → FC	0.087	0.66	0.509	Not supported
H_2		DSC → III	0.65	11.67	<0.001	Supported
H_3		III → FC	0.508	4.08	<0.001	Supported
H_4		DSC → III → FC (Mediation)	-	-	-	Supported (full mediation)
Sensitivity analysis						
Path		Full data β	Cleaned data β	Delta β	Significance (both)	
DSC → III		0.652	0.664	+0.012	Significant (p<0.001)	
DSC → FC		0.087	-0.007	-0.094	Not significant (p=0.509)	
III → FC		0.508	0.593	+0.094	Significant (p<0.001)	
Construct		R^2 (full data)	R^2 (Cleaned data)	Delta R^2		
Inside-In Innovation (III)		0.425	0.441	+0.016		
Firm Competitiveness (FC)		0.323	0.346	+0.023		
Detailed path coefficients (with controls)						
Path		Base estimate β	With controls β	Delta β	t-base	t-control
DSC → III		0.652	0.613	-0.039	11.88	7.95

DSC → FC	0.087	0.094	+0.007	0.67	0.74
III → FC	0.508	0.509	0.00	4.16	4.22
R^2 Comparison (base without controls and with controls)					
Construct	R^2 (Base)	R^2 (With controls)	Delta R^2		
III	0.425	0.439	+0.014		
FC	0.323	0.360	+0.037		

6.4.1 Model explanatory power

Coefficient of determination (R^2), Cross-validated redundancy (Q^2) and Effect sizes (f2) were metrices used to test for testing how well the statistical model accounts for variance in the dependent variable. The Coefficient of determination results were R^2 (III) = 0.425 and R^2 (FC) = 0.323 meaning that means that the model demonstrates moderate explanatory power, confirming that these constructs meaningfully contribute to how firms sense opportunities, innovate internally, and sustain competitiveness.

The Cross-validated redundancy (Q^2) was relatively higher Q^2 for Inside-In Innovation suggesting that the model predicts this construct particularly well, while the positive Q^2 for firm competitiveness confirms adequate predictive relevance at the outcome level. Collectively, these findings affirm that the structural model has substantial predictive capability and external validity.

The findings of Effect sizes (f^2) indicate that dynamic sensing capabilities have a strong and meaningful influence on Inside-In Innovation (large effect). This is aligned with the theoretical perspective that sensing capabilities offer valuable insights and necessitate internal resource investment to develop products or services that are tailored to meet customer needs effectively (Goerzig & Bauernhansl, 2018). Furthermore, Bayighomog Likoum et al. (2020) suggests that insights gathered from environmental scanning should inform internal decisions on emerging opportunities and threats relating to technology and market changes.

The small effect of Inside-In Innovation on firm competitiveness indicates that while innovation contributes to competitiveness, it "probably" does so alongside other factors not captured in the model. This empirical finding is aligned with theoretical perspectives. Candi and Kahn (2025) argue that high performing firms deploy open innovation to drive competitiveness, while Pundziene et al. (2022) postulate that Inside-In Innovation has potential to compliment Outside-In and Inside-Out Innovation. The negligible direct effect of dynamic sensing capabilities on firm competitiveness contradicts the scholarly work, which makes an assertion that sensing directly enhances performance (Fainshmidt et al., 2019; Al Dhaheri et al., 2024; Umulkher & Gichinga, 2024).

Therefore, observed effect sizes align with Teece's (2020) assertion that the open innovation and dynamic capabilities frameworks are inherently complementary. Teece (2020) argues that firms must develop the ability to sense, seize, and transform in response to environmental shifts to maintain competitiveness. Open innovation reflects these processes by enabling firms to access and integrate external knowledge effectively. Empirical evidence supports this theoretical linkage, as indicated by the large effect size between dynamic sensing capabilities (DSC) and Inside-In Innovation (III) indicating strong influence, a small effect size between III and Firm Competitiveness (FC) suggests Inside-In Innovation requires complementary open innovation archetypes required to strongly influence firm competitiveness, and a negligible effect size between DSC and FC reinforces a need for a mediation construct.

6.4.4 Path coefficients (hypotheses testing)

6.4.4.1 Hypothesis 1 (H1) analysis

It was hypothesised in Chapter 3 that Dynamic Sensing Capabilities (DSC) positively influence Firm Competitiveness (FC). That is, H_1: DSC → FC.

The results presented in Chapter 5 indicate that the hypothesised direct relationship between dynamic sensing capabilities (DSC) and firm competitiveness (FC) lacks statistical support. This means that the DSC → FC path is not statistically significant based on the p-value and confidence interval ($\beta = 0.087$, $p = 0.509$). According to Teece (2020), dynamic sensing is the initial phase of the triad process, i.e. sensing, seizing, and transformation that enables dynamic capabilities to be deployed to achieve competitiveness. Therefore, the path outcomes substantiate the theoretical underpinning that sensing alone is not sufficient to yield firm competitiveness. The findings also indicate that although dynamic sensing is applied within the energy industry, there appears to be a disconnect between its application and the ability to translate it into tangible competitive advantage. These findings challenge the position advanced by Umulkher and Gichinga (2024) who assert that sensing capabilities have a direct and positive influence on competitiveness.

However, the evidence aligns with the perspective articulated by Eisenhardt and Martin (2000), Zott (2003), and Al Dhaheri et al. (2024) who argue that sensing capabilities in isolation are insufficient to secure competitive advantage. Rather, their effectiveness is contingent upon complementary processes and the contextual dynamism of the environment. Chowdhury and Quaddus (2021) reinforce this view by emphasising the necessity of deploying dynamic capabilities holistically to enhance firm performance.

Furthermore, it must be noted that average variance extracted (AVE) for firm competitiveness was less than 0.5 which could potentially weaken the relationship between dynamic sensing capabilities and firm competitiveness in the structural model due to the latter construct being not well captured (Fornell & Larcker, 1981).

6.4.4.2 Hypothesis 2 (H_2) analysis

It was hypothesised in Chapter 3 that Dynamic Sensing Capabilities (DSC) positively influence Inside-In Innovation (III). That is, H_2: DSC → III.

The results presented in Chapter 5 indicate that the hypothesised direct relationship between dynamic sensing capabilities (DSC) and Inside-In Innovation (III) is statistically supported.

These findings are articulated through dynamic capabilities and open innovation frameworks for dynamic sensing capabilities and Inside-In Innovation. According to scholarly literature, dynamic capabilities framework articulates the dynamism of both external and internal firm ecosystem as well as the ability to renew firm competencies to reposition in equivalence to the change anticipated in the operating context (Teece et al.,1997; Mansouri et al., 2022). Teece (2007) further suggests that sensing capabilities are grounded on the firm process and structures that internalise insights emerging form the ecosystem displaying agility in strategic responses and improving competitiveness. These theoretical arguments are well supported by practical evidence: respondents strongly agreed that environmental scanning and opportunity selection are actively managed in their firms, and that these processes are supported internally through organisational learning capabilities, knowledge and asset sharing, communication loops, and innovation investments and process. However, the respondents provided neutral responses on new ideas and employee collaboration. These findings are two folds:

- Challenges open innovation framework which although it acknowledges deployment of innovation through effective integration and utilisation of both internal and external sources of knowledge and innovation, it remains mute on Inside-In Innovation process nor individual contribution of these antecedents of Inside-In Innovation (Chesbrough, 2003).
- Study corroborates scholarly perspectives that position sensing capabilities as internally embedded through Inside-In Innovation, operationalised through mechanisms such as effective communication, cross-functional collaboration,

idea generation, knowledge and asset sharing, and organisational learning capabilities (Harvey, 2025); however, our results show neutrality when it comes to employee collaboration and new ideas creating an emergent gap in the energy industry.

Shani et al. (2025) argue that continuous adaptation in firms due to turbulent ecosystem requires feedback loops and internal communication as mechanisms for sensing shifts, while Stoeber and Kanbach (2025) postulate that sensing capabilities are closely linked to open innovation activities such as permeable boundaries, communication loops, and collaborative ecosystem. The study findings support these theoretical findings; however, gaps in communication visibility gaps and disconnect between ideation and implementation weaken collaborative outcomes and presents risks in strategic alignment.

Furthermore, Diaz et al. (2017) postulate that firms with limited resource can leverage employee motivation and internal collaboration networks to enable collaboration, while Steiber and Alänge (2020) argue that such firms should consider having dedicated innovation units or joint teams with other firms to seize opportunities for joint benefits. The findings of the study are aligned to these theoretical perspectives. However, restrictive reward systems and absence of innovation platforms weaken team cohesion.

Stoeber and Kanbach (2025) also argue that knowledge is co-shaped by external and internal interactions due to its fluidity posture and in absence of strong internal capabilities, external knowledge may be perceived as hindrances for innovation. This theoretical posture is aligned with practical evidence from the energy sector, as learning capabilities are embedded across the organisation, reinforcing the interdependence of dynamic sensing and learning as drivers of innovation.

Therefore, though sensing capabilities as internally embedded through Inside-In Innovation, there are clear gaps in the Inside-In mechanism impeding effective communication, cross-functional collaboration, idea generation, and knowledge and asset sharing in the energy industry. However, learning capabilities are fully embedded throughout the energy industry, reinforcing the argument that dynamic sensing and learning are interdependent drivers of innovation and competitiveness.

6.4.4.3 Hypothesis 3 (H_3) analysis

It was hypothesized that Inside-In Innovation (III) positively influences Firm Competitiveness (FC). That is, H_3: III → FC.

The results presented in Chapter 5 indicate that the hypothesised direct relationship between Inside-In Innovation (III) and Firm Competitiveness (FC) is statistically supported. That is, III → FC is statistically supported because the p-value < 0.001 and the confidence interval (0.269 to 0.748) does not cross zero. These findings are articulated through dynamic capabilities and open innovation frameworks.

Teece et al. (1997) refers to dynamic capabilities as the ability to integrate, build, and reconfigure internal and external competencies at the pace of changes in the ecosystem to ensure competitiveness, and this is supported by the empirical evidence from the study that integration and reconfiguration of resources is done through Inside-In Innovation processes. Chesbrough (2003) argues that open innovation is supported by external-in, inside-out, and coupled innovations, with supporting mechanisms, which align with inside-in processes , encapsulating knowledge flows, etc. This is supported by survey outcomes on positive perceptions on processes on learning capabilities, knowledge and asset sharing, and innovation investments and process.

Furthermore, recent scholarship purport that innovation improves financial performance and firm competitiveness (Agazu & Kero, 2024; Sukumar et al., 2020; Obeidat et al., 2021). However, such companies ought to have processes and structures that foster innovation to be in a better position to compete with their peers (Sukumar et al., 2020), while other scholars suggest that innovation improves financial performance and firm competitiveness (Agazu & Kero, 2024; Sukumar et al., 2020; Obeidat et al., 2021).

The practical evidence show that leadership and cultural factors promote innovation and structural mechanisms for ideas logging exist in the energy industry; however, there are pertinent gaps in their internal processes. This includes communication visibility which impedes on collaboration; disconnect between ideation and implementation which shows weakness in the mechanism leading to failure in producing tangible innovation outcomes; and restrictive reward and recognition policies and the absence of innovation platform ecosystems, both of which stifle collaborative potential. However, these results may have been skewed by majority being in management due to sampling bias introduced by purposive sampling. Furthermore, the respondents indicate that sales have partially grown over the past three years.

Ferreira et al. (2020) note that innovation outputs are characterised by shortened product process time in relation to the competitors, strong market performance of new products, and timeously substituting outdated products resulting in better firm performance. The findings partially align with this perspective. The respondents indicate that enterprise's new products or services received better evaluations than the new products and services of our competitors. However, evidence also revealed areas of divergence. The respondents partially disagree that sales of their enterprise have risen faster than sales of their competitors; their enterprise creates more products/services per year than their competitors and market share has improved over the past three years. Additionally, Bibi et al. (2020) claim firm competitiveness is also driven by organisational learning and employees' inclination to innovate. The findings confirm that learning capabilities are embedded throughout the organisation.

Therefore, even though the energy industry presents inside-in attributes, there are clear gaps in their internal processes that are hindering internal innovation hence input efforts partially translate into competitiveness deviating from theoretical expectations.

6.4.4.4 Hypothesis 4 (H_4) analysis

It was hypothesised that Inside-In Innovation (III) mediates the relationship between Dynamic Sensing Capabilities (DSC) and Firm Competitiveness (FC). That is, H_4: Mediation (DSC → III → FC).

The results of H_4 analysis show that indirect path (DSC → III → FC) was considered statistically supported while the direct path (DSC → FC) was considered not statistically supported, therefore, this indicates full mediation. These findings supports scholarly literature that suggests that "to remain competitive over time, a company must be able to move quickly in response to major changes in society, technology, competition, regulation, labour markets, and myriad other areas", and "strong dynamic capabilities enable effective open innovation practices" (Teece, 2020: 28-29). In addition, the findings are aligned with Sarwar et al. (2023) postulate that dynamic capabilities systematically solve company's issues through timely and market related decisions, improving and developing new organisational competencies, and ensuring that it is future ready and thus generating long-term competitiveness.

Our theoretical grounding purports that the core micro-foundations of dynamic capabilities, i.e., sensing, seizing, and transforming, enable firms to continuously identify external opportunities and threats detect, mobilise resources, and implement strategic responses for value creation and continuously adapt to changing environments (Teece, 2007). The practical evidence affirms this posture by indicating that on a regular basis, local and international market trends are assessed; technology developments are followed; and customers' experiences and emerging needs are assessed. Furthermore, enough time is spared to observe and evaluate business environment, and environmental changes seem to be noticed early. The respondents also agreed that there is orientation towards high finance value projects even if the projects are risky. Moreover, leadership champions sponsorship for new opportunities; and leadership encourages diversity of thoughts to ensure richness of the opportunity funnel.

Concurrently, Bayighomog Likoum et. al. (2020) argue that sensing enables firms to gather insights of their operating context and internally make decisions pertaining to the market and technology. This was achieved by demonstrating that dynamic sensing capabilities have an influence on Inside-In Innovation. However, the researcher is also cognisant that some firms may only be doing market scanning hence there seems to be a disconnect between insights from the energy ecosystem and internal decisions made. Furthermore, the results demonstrated that Inside-In Innovation has influence on the firm competitiveness; however, direct influence of dynamic sensing capabilities on firm competitiveness could not be established. Therefore, full mediation role of Inside-In Innovation on the relationship between dynamic sensing and firm competitiveness was established.

6.5 Theoretical implications

Inside-In Innovation is a proven driver of firm competitiveness, firmly supported by empirical evidence and grounded in dynamic capabilities and open innovation frameworks. Therefore, Inside-In Innovation provides mechanism of transforming resource advantage into competitive advantage and deeper reflections and reconfiguration of internal resources, as well as processes enabling innovation, in so doing, closing the current gap in open innovation archetypes fail to explain dynamic capabilities mechanism (Wang & Ahmad, 2017; Zadegan et al., 2025). This mechanism is characterised by communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning capability processes.

However, the effect of Inside-In Innovation on Firm Competitiveness was small but meaningful, suggesting that while innovation enhances competitiveness, its influence operates alongside other strategic factors beyond this model. These strategic factors are other archetypes of open innovation, i.e., Outside-In, Inside-Out, coupled, and Outside-Out Innovation which complement each other through effective integration and utilisation of both internal and external sources of knowledge and innovation, broadening and enriching open innovation paradigm (Chesbrough, 2003; Pundziene et al., 2022; Gutmann, 2023).

Dynamic sensing capabilities does not positively influence firm competitiveness, unless complementary structural and processes are leveraged, i.e., Inside-In Innovation. This is aligned to Cavusgil and Deligonul (2025), positing that dynamic capabilities enable firms to adapt, foster innovation, and improve resilience.

6.6 Business implications

Actionable insights for practitioners that enhance innovation and mitigate against siloed practices which impede energy firms' ability to adopt critical technologies, thereby constraining their capacity to achieve competitive advantage have been established in the study. These are communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning capability processes; however, management need to ensure full deployment of these antecedents to ensure realisation of innovation objectives.

6.7 Contextual implications

Although dynamic sensing is applied in the energy industry, its translation into tangible competitive advantage remains limited due to weak integration of external information with internal resources (Bayighomog Likoum et al., 2020). This is because of emergent gaps in operationalisation mechanisms of Inside-In Innovation such as employee collaboration and idea generation (Harvey, 2025).

Findings indicate that even though leadership and cultural factors promote innovation, there are gaps in communication visibility and disconnect between ideation and implementation which undermine collaborative outcomes. However, respondents were largely in management roles and could have been subjective in responding to such an enquiry. Structural mechanisms for idea logging exist, the disconnect between ideation and implementation shows weakness in the mechanism leading to failure in producing tangible innovation outcomes. Failure to bridge these gaps restricts the competitiveness benefits of individual creativity, creating tension between knowledge sharing and risks of misalignment.

Successful innovation investments require not only financial resources but integrated processes and strategic clarity. Learning capabilities are embedded across the organization, reinforcing the interdependence of dynamic sensing and learning as drivers of innovation. However, restrictive reward systems and absence of innovation platforms weaken team cohesion, echoing Van der Voet and Steijn's (2021) caution that visionary leadership is essential for sustaining collaboration.

6.8 Management implications

While leadership and cultural enablers exist, structural and process gaps such as poor communication visibility, weak ideation-to-implementation linkage, and restrictive reward systems significantly undermine the full realisation of innovation benefits. To achieve sustained market advantage, organisations must integrate resources and processes strategically, ensuring that embedded learning and sensing capabilities translate into measurable competitive outcomes.

Gutmann (2023) argues that large firms are struggling to deliver on open innovation objectives due to challenges in internal knowledge flows. In addition, Malisić et al. (2025) highlights that internal innovation cannot exist in absence of dynamic capabilities, while Mathias et al. (2024) argue that innovative firms internalise external trends and integrate them in their new product development and processes. Similarly, Younas (2024) posits that research and development projects typically have prolonged lead times, and internal innovation has the potential to accelerate the commissioning of such projects.

Nonetheless, Pundziene et al. (2022) argue that firms with minimal "exchange of knowledge and other valuable resources between internal units", their open innovation is likely to be impeded (p. 171). This highlights the importance of Inside-In Innovation in the internal innovation process and mechanism of dynamic capabilities. In addition, Pitelis et al. (2024) posit that sensing, seizing of opportunities, and transformation of resource base are critical elements of dynamic capabilities. Furthermore, dynamic sensing capabilities enables insights gathering on customer needs, competitors, and technology trends (Harvey, 2022).

6.9 Methodological implications

Though the study used modified existing validated methodological scales, measurement model assessment was done to ensure validity and reliability of the survey instrument. This was achieved through testing for internal consistency reliability, i.e., Cronbach's alpha (CA) and composite reliability (CR); convergent validity; and discriminant validity which were within acceptable limits. These findings strengthened confidence in the measurement model and showed that the constructs, Dynamic Sensing Capabilities, Inside-In Innovation, and Firm Competitiveness capture unique conceptual domains. Furthermore, purposive sampling introduced sampling bias which could potentially undermines generalisability.

6.10 Revised Conceptual model

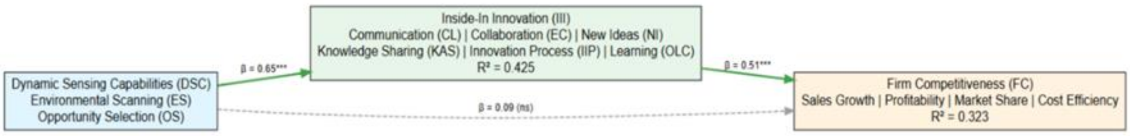

Figure 2: Revised conceptual model

The study findings show that firms with Dynamic Sensing Capabilities, particularly, environmental scanning and opportunity selection, tend to positively influence Inside-In Innovation ($\beta = 0.65$, $p < 0.001$). Additionally, Inside-In Innovation has positive influence on Firm Competitiveness ($\beta = 0.51$, $p < 0.001$). However, the direct link between Dynamic Sensing Capabilities and Firm Competitiveness ($\beta = 0.09$, $p = 0.509$) was not significant. This suggests that sensing external opportunities positively influences competitiveness only when those insights are channelled through Inside-In Innovation processes.

Overall, the model explains 42.5% of the variance in Inside-In Innovation and 32.3% in Firm Competitiveness, confirming the full mediation effect and highlighting how innovation acts as the bridge between sensing and performance within the dynamic capabilities' framework.

6.11 Conclusion

The aim of the study was to determine the influence dynamic sensing capabilities (environmental scanning and opportunity selection) on firm competitiveness and the mediation role of Inside-In Innovation (communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning).

In this chapter, demographic data of the respondents was articulated; Descriptive statistics discussed; Measurement model (outer model) assessment done; and lastly, Structural model (inner model) assessment and hypotheses testing completed. This resulted in a revised conceptual model that summarises the study outcome.

CHAPTER 7: CONCLUSION

7.1 Overview of the study

7.1.1 Research context and significance

The aim of the study was to determine the influence of dynamic sensing capabilities on firm competitiveness and the mediation role of Inside-In Innovation. The study was done within the context of the South African energy companies, an industry undergoing profound structural and technological shifts. The research aimed at delivering actionable insights for practitioners to enable robust innovation strategies that enhance firm competitiveness amid rapid change in the ecosystem. Furthermore, the research anticipated to close the theoretical divide in the mechanisms underpinning dynamic capabilities. Existing archetypes of open innovation fall short of explaining dynamic capabilities' "mechanisms of transforming resource advantage into competitive advantage" because they omit Inside-In Innovation. Hence, the objective was to determine mechanisms underpinning Inside-In Innovation and its integration within dynamic capabilities frameworks.

7.1.2 Research Question

The main research question for this study was: What are the mechanisms underpinning Inside-In Innovation and its integration within dynamic capabilities frameworks?

7.1.3 Methodological Approach

Positivism paradigm deploying deductive or quantitative research approach was deployed. Existing validated survey instruments were adopted and modified to provide meaningful analysis closer to previous studies

7.2 Principal findings

7.2.1 Hypothesis H1

The hypothesised direct relationship between dynamic sensing capabilities (DSC) and firm competitiveness (FC) lacks statistical support. This means that the DSC → FC path is not statistically significant based on the p-value and confidence interval ($\beta = 0.087$, p

= 0.509). Though this is aligned with the theoretic underpinning that dynamic sensing is the initial phase of the triad process, i.e., sensing, seizing, and transformation that enables dynamic capabilities to be deployed to achieve competitiveness, it deviates from other scholarly assertions regarding direct relationship between the two constructs. However, lower Convergent validity of firm competitiveness could have weakened the construct skewing the model outcomes.

7.2.3 Hypothesis H2

The hypothesised direct relationship between dynamic sensing capabilities (DSC) and Inside-In Innovation (III) is statistically supported. Theory depicts that the dynamism of both external and internal firm ecosystem as well as the ability to renew firm competencies to reposition in equivalence to the change anticipated in the operating context; furthermore, sensing capabilities are grounded on the firm process and structures that internalise insights emerging form the ecosystem. This is in sync with practical evidence that respondents strongly agreed that environmental scanning and opportunity selection are actively managed in their firms and that is supported internally through organisational learning capabilities, knowledge and asset sharing, communication loops, and innovation investments and process, except new ideas and employee collaboration. However, these findings challenge open innovation framework to recognise Inside-In Innovation in the open innovation process and quantify individual contribution of these antecedents of Inside-In Innovation towards enabling innovation.

7.2.3 Hypothesis H3

The hypothesised direct relationship between Inside-In Innovation (III) and Firm Competitiveness (FC) is statistically supported; however, the effect sizes are small indicating that complementary elements of open innovation may be required to strengthen the relationship. Teece et al. (1997) refers to dynamic capabilities as the ability to integrate, build and reconfigure internal and external competencies at the pace of changes in the ecosystem to ensure competitiveness, Chesbrough (2003) argues that open innovation is supported by external-in, inside-out, and coupled innovations with supporting mechanisms which aligns with inside-in processes, encapsulating knowledge flows, etc. These theoretical underpinnings align with empirical evidence from the study that integration and reconfiguration of resources is done through Inside-In Innovation processes and survey outcomes on positive perceptions on processes on learning capabilities, knowledge and asset sharing, and innovation investments and process.

7.2.4 Hypothesis H4

The results of H4 analysis show that indirect path (DSC → III → FC) was considered statistically supported while the direct path (DSC → FC) was considered not statistically supported; therefore, this indicates full mediation. Teece (2007) argues that the core micro-foundations of dynamic capabilities, i.e., sensing, seizing, and transforming, enable firms to continuously identify external opportunities and threats detect, mobilise resources, and implement strategic responses for value creation and continuously adapt to changing environments and this has been supported by the empirical evidence.

7.3 Theoretical contribution

The study makes significant theoretical contributions to dynamic capability framework and open innovation by revealing the mechanisms underpinning Inside-In Innovation and integrating these into the framework, thereby addressing a critical theoretical gap. This gap emerged from Sahakian and Jouini's (2023) assertion of the urgent need to renew existing resource bases to enable capability transformation, compared with scholarly conceptualisations of Inside-In Innovation as a process of deep reflection and reconfiguration of internal resources and processes to foster innovation (Teece, 2020; Pundziene et al., 2022; Zhang et al., 2023; Zadegan et al., 2025).

The research was anchored on the dynamic capabilities and open innovation frameworks. Teece et al. (1997) posit that in an evolving technological environment, the firm's competitive advantage depends on its ability to leverage its internal resources. The scholars further argue that dynamic capabilities approach is grounded on the firm's ability to renew competencies and achieve equivalence as the environment of business changes, triggering innovation and timely adapting, reconfiguring, and integrating resources. Furthermore, scholarly literature posit that current global dynamics require firms to be nimble enough to adapt to maintain their competitiveness; however, the mechanics of the adaptation urgency were not interrogated (Sambamurthy et al., 2003; Wilden et al., 2013; Correia et al., 2021). According to the scholarly literature, Inside-In Innovation enables permeability of innovative capabilities internally within an organisation, breaking internal silos to achieve innovation impact (Gutmann et al., 2023; Pundziene et al., 2022).

The study's findings show that firms with Dynamic Sensing Capabilities, particularly environmental scanning and opportunity selection, positively influence Inside-In Innovation ($\beta = 0.65$, $p < 0.001$). Additionally, Inside-In Innovation has positive influence on Firm Competitiveness (β = 0.51, $p < 0.001$). However, the direct link between Dynamic Sensing Capabilities and Firm Competitiveness (β = 0.09, $p = 0.509$) was not significant. This suggests that sensing external opportunities positively influences competitiveness only when those insights are channelled through Inside-In Innovation processes.

Furthermore, Inside-In Innovation provides mechanism of transforming resource advantage into competitive advantage and deeper reflections and reconfiguration of internal resources and processes enabling innovation, in so doing, closing the current gap in open innovation archetypes failure to explain dynamic capabilities mechanism. This mechanism is characterised by communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning capability processes. Additionally, Inside-In Innovation compliments other archetypes of open innovation through integration and utilisation of both internal and external sources of knowledge and innovation, broadening and enriching open innovation paradigm.

7.4 Management contribution

Management should integrate mechanisms of Inside-In Innovation (i.e., communication loop, employee collaboration, new ideas, knowledge and asset sharing, innovation investments and process, and organisational learning) into their open innovation process while actively monitoring their ecosystem to ensure Firm Competitiveness.

7.5 Contextual contribution

The energy industry is well invested in sensing capabilities and needs to close emergent gap in fully operationalising mechanisms of Inside-In Innovation such as reward systems to encourage employee collaboration and innovation platforms for idea generation. Structural mechanisms for idea logging exist; however, the disconnect between ideation and implementation require mitigation.

7.6 Methodological contribution

Modified measurement scales can be used for future studies; however Firm Competitiveness variables will have to be reassessed.

7.7 Limitations

The study has limitations that can be improved in further research. Cross-sectional and quantitative study does not observe a phenomenon over time and lacks depth of insights gathered. Purposive sampling introduces sampling bias into the model.

Convergent validity was established using average variance extracted which was above 0.50 for all constructs except for Firm Competitiveness which means that construct explains less than half of the variance in its indicators. However, the construct was kept in the model due to high composite reliability.

The discriminant validity of Communication Loop and Employee Collaboration and Knowledge and Asset Sharing with Innovation Investment and Process latent variables was only confirmed using the Fornell–Larcker criterion and its associated matrix results, and not HTMT criterion signalling potential multicollinearity issues due to the conceptual proximity of the constructs.

7.8 Future research

Although our paper addresses several significant issues related to dynamic sensing capabilities, Inside-In Innovation and Firm Competitiveness, future studies are recommended to contribute towards quantification of the Inside-In Innovation required enabling dynamic sensing and open innovation archetypes. A longitudinal study design to empirically confirm causality and assess innovation and firm performance outcomes over time is recommended.

7.9 Final remarks

In conclusion, our empirical research helps provide mechanism of transforming resource advantage into competitive advantage and deeper reflections and reconfiguration of internal resources and processes enabling innovation, in so doing, closing the current gap in open innovation archetypes' failure to explain dynamic capabilities mechanism.

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APPENDICES

Annexure A: Sample size calculation

$n=((N*Z^2*p(1-p))/(e^2(N-1)+Z2*p(1-p))$

Where:

- n = required sample size
- N = population size (120 000)
- Z = Z-score for confidence level (e.g., 1.96 for 95%)
- p = estimated proportion (often 0.5 for maximum variability)
- e = margin of error (e.g., 0.05 for ±5%)

Therefore, $n= (120{,}000*(1.96)^2*0.5(1-0.5))$
$/((0.05)^2(120{,}000-1)+(1.96)^2*0.5(1-0.5)) = 383$ respondents

Annexure B: Ethical clearance

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Lebogang Sennanye,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Annexure C: Survey questionnaire

SECTION A: CONSENT SECTION

Dear Respondent

I am MPhil Corporate Strategy student at GIBS conducting research on "Influence Of Dynamic Sensing Capabilities On Firm Competitiveness And Mediation Role Of Inside-In Innovation". To that end, you are asked to complete a survey relating to my topic.

The survey should take no more than 20 minutes. All information collected will be kept confidential and no names will be collected. Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact my supervisors or me. Our details are provided below.

Researcher name:	Ms Lebogang Sennanye
Email:	25417292@mygibs.co.za
Phone:	[redacted]

Research supervisor name:	Prof Manoj Chiba
Email:	chibam@gibs.co.za
Phone:	[redacted]

Research supervisor name:	Dr Adetunji Adegbesan
Email:	adegbesana@gibs.co.za
Phone:	[redacted]

SECTION B: DEMOGRAPHIC QUESTIONS

Please answer the following demographic questions by clicking on an answer that applies. Your responses will remain confidential and will be used for academic research purposes only.

Age:
☐ Under 18
☐ 18-24
☐ 25-34
☐ 35-44
☐ 45-54
☐ > 55

Gender:
☐ Male
☐ Female
☐ Non-binary
☐ Prefer not to say

Education Level:
☐ No formal education
☐ Matric or equivalent
☐ Diploma
☐ Bachelor's degree
☐ Master's degree
☐ Doctorate or higher

Work experience:
☐ 0-4 years
☐ 5-9 years
☐ 10-15
☐ > 15 years

Work title/ Role:
☐ Manager
☐ Senior Management
☐ Executive
☐ Other

Nature of your role
☐ Technical
☐ Strategic
☐ Other………………….

Company size
☐ 0- 500 employees
☐ 501- 5000 employees
☐ > 5000 employees

Company sector
☐ Energy
☐ Others……………..

Energy value chain play
☐ Upstream
☐ Midstream
☐ Downstream
☐ Integrated

SECTION C: SURVEY QUESTIONNAIRE

Please indicate your level of agreement with the following statements regarding practices in your company by selecting the appropriate option.

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

SECTION C1.1: Dynamic sensing capability: Environmental scanning variable

1. On a regular basis, local and international market trends are assessed [1 2 3 4 5]

2. Technology developments are followed [1 2 3 4 5]

3. Customers' experiences and emerging needs are assessed [1 2 3 4 5]

4. Enough time is spared to observe and evaluate business environment [1 2 3 4 5]

5. Forthcoming environmental changes are noticed early [1 2 3 4 5]

SECTION C1.2: Dynamic sensing capability: Opportunity selection variable

1. There is orientation towards high finance value projects even if the projects are risky [1 2 3 4 5]

2. Bold strokes are taken when searching for new opportunities [1 2 3 4 5]

3. New and original ideas are encouraged in the organization [1 2 3 4 5]

4. Leadership champions sponsorship for new opportunities [1 2 3 4 5]

5. Leadership encourages diversity of thoughts to ensure richness of the opportunity funnel [1 2 3 4 5]

SECTION C2: Firm competitiveness

1. Sales growth over the past three years [1 2 3 4 5]

2. Sales of our enterprise rise faster than sales of our competitors [1 2 3 4 5]

4. Our enterprise creates more products/services per year than our competitors [1 2 3 4 5]

5. Our enterprise's new products/services receive better evaluations than the new products/services of our competitors [1 2 3 4 5]

6. Market share has improved over the past three years [1 2 3 4 5]

7. Costs has been managed/ contained over the past three years [1 2 3 4 5]

SECTION C3.1: Inside-in innovation: Communication loop

1. Communication among business units and project teams are timely and efficient [1 2 3 4 5]
2. Innovation progress dashboards and other communication tools available and visible to employees across the organization [1 2 3 4 5]
3. Leadership demonstrates culture of innovation, i.e. "tone at the top" [1 2 3 4 5]
4. The frequency of communication supports innovative culture [1 2 3 4 5]
5. Bottom-up communication on innovative ideas is enabled through supporting tools and systems [1 2 3 4 5]

SECTION C3.2: Inside-in innovation: Employees collaboration

1. Coordination among business units and project teams are timely and efficient [1 2 3 4 5]

2. Performance review process encourages collaboration across teams [1 2 3 4 5]

3. Rewards/ recognitions policy encourages collaboration across teams [1 2 3 4 5]

4. There is intra-organisational collaboration across all levels [1 2 3 4 5]

5. Innovation platform ecosystems enable collaboration [1 2 3 4 5]

SECTION C3.3: Inside-in innovation: New ideas

1. On a regular basis, new ideas are logged onto the innovation system [1 2 3 4 5]

2. Innovation events are held to inspire idea generation across organization [1 2 3 4 5]

3. At least one idea per annum is incubated through the innovation cycle [1 2 3 4 5]

4. Official internal innovation networks established to encourage new ideas creation [1 2 3 4 5]

5. Ideation platforms accessible to teams across the organization [1 2 3 4 5]

SECTION C3.4: Inside-in innovation: Knowledge and assets sharing

1. On a regular basis, knowledge sharing sessions on latest innovation developments are held [1 2 3 4 5]

2. There is knowledge centered culture in the organization [1 2 3 4 5]

3. Leadership encourages knowledge sharing on innovation developments [1 2 3 4 5]

4. Knowledge ecosystems, e.g., databases, newsletters, etc. are accessible across the organization [1 2 3 4 5]

5. Employees partake on the latest innovation discussions [1 2 3 4 5]

6. Assets are made available for pilot phase of projects [1 2 3 4 5]

7. Dedicated assets for innovative projects are sufficiently utilized [1 2 3 4 5]

8. Governance processes support timely use of assets for pilot projects [1 2 3 4 5]

9. Teams across the organization have access to assets needed for their pilot projects [1 2 3 4 5]

10. Assets required for pilot projects are sufficiently maintained [1 2 3 4 5]

SECTION C3.5: Inside-in innovation: Innovation investments and process

1. Existing processes and decision-making tools support each stage of innovation development [1 2 3 4 5]

2. It is clearly set when to proceed with innovative product/ service development, when to cut it, increase/decrease investment, etc. [1 2 3 4 5]

3. Existing innovation project management tools support to achieve satisfactory innovation speed, return of investment and outcomes [1 2 3 4 5]

4. There is annual budget allocation that support innovation activities [1 2 3 4 5]

5. The company has business intelligence and analytics capabilities [1 2 3 4 5]

SECTION C3.6: Inside-in innovation: Organisational learning capability

1. Employees are proficient in project management [1 2 3 4 5]

2. Our organization offers rotation/ secondment opportunities to employees [1 2 3 4 5]

3. There is bottom-up learning in the organization [1 2 3 4 5]

4. Team learning and unlearning is encouraged across the organization [1 2 3 4 5]

5. Learning capabilities are embedded across all levels [1 2 3 4 5]

Annexure D: R code

```
################## Rcode used  for R2, f2 and Q2
outputs#############################
# --------- 1) R² for each full / reduced model ----------
# (i) Path DSC → III
m_full_III     <- lm(III ~ DSC, data = Z)            # full
R2_full_III    <- summary(m_full_III)$r.squared       # with DSC
R2_red_III     <- 0                                 # intercept-only has R² = 0
f2_DSC_on_III  <- (R2_full_III - R2_red_III) / (1 - R2_full_III)

# (ii) Paths to FC
m_full_FC      <- lm(FC ~ DSC + III, data = Z)
R2_full_FC     <- summary(m_full_FC)$r.squared

m_red_III_on_FC <- lm(FC ~ DSC, data = Z)            # remove III
R2_red_III_on_FC <- summary(m_red_III_on_FC)$r.squared
f2_III_on_FC     <- (R2_full_FC - R2_red_III_on_FC) / (1 - R2_full_FC)

m_red_DSC_on_FC <- lm(FC ~ III, data = Z)            # remove DSC
R2_red_DSC_on_FC <- summary(m_red_DSC_on_FC)$r.squared
f2_DSC_on_FC     <- (R2_full_FC - R2_red_DSC_on_FC) / (1 - R2_full_FC)

# --------- 2) Tidy table ----------
f2_tbl <- data.frame(
```

```
  Path = c("DSC → III", "III → FC", "DSC → FC"),
  f2   = round(c(f2_DSC_on_III, f2_III_on_FC, f2_DSC_on_FC), 3),
  Magnitude = cut(c(f2_DSC_on_III, f2_III_on_FC, f2_DSC_on_FC),
                  breaks = c(-Inf, .02, .15, .35, Inf),
                  labels = c("negligible","small","medium","large"))
)
print(f2_tbl)


set.seed(123)

q2_kfold <- function(y, X, k = 10) {
  n <- length(y)
  folds <- sample(rep(1:k, length.out = n))
  press <- 0
  for (i in 1:k) {
    idx_test  <- which(folds == i)
    idx_train <- setdiff(seq_len(n), idx_test)
    dat_tr <- data.frame(y = y[idx_train], X[idx_train, , drop = FALSE])
    dat_te <- data.frame(y = y[idx_test],  X[idx_test,  , drop = FALSE])
    fit    <- lm(y ~ ., data = dat_tr)
    pred   <- predict(fit, newdata = dat_te)
    press  <- press + sum((dat_te$y - pred)^2)
  }
  sst <- sum( (y - mean(y))^2 )
  1 - press/sst
}


set.seed(123)

q2_kfold <- function(y, X, k = 10) {
  stopifnot(length(y) == nrow(X))
  n <- length(y)
  folds <- sample(rep(1:k, length.out = n))
  press <- 0

  for (i in 1:k) {
    idx_te  <- which(folds == i)
    idx_tr  <- setdiff(seq_len(n), idx_te)

    df_tr <- data.frame(y = y[idx_tr], X[idx_tr, , drop = FALSE], check.names =
FALSE)
    df_te <- data.frame(       X[idx_te, , drop = FALSE], check.names = FALSE)

    fit  <- stats::lm(y ~ ., data = df_tr)
    pred <- stats::predict(fit, newdata = df_te)  # force stats::predict.lm
    press <- press + sum( (y[idx_te] - pred)^2 )
  }

  sst <- sum( (y - mean(y))^2 )
```

```
  1 - press/sst
}

# Q² values
Q2_III <- q2_kfold(y = Z$III, X = data.frame(DSC = Z$DSC))
Q2_FC  <- q2_kfold(y = Z$FC,  X = data.frame(DSC = Z$DSC, III = Z$III))
Q2_tbl <- data.frame(
  Construct = c("III","FC"),
  Q2 = round(c(Q2_III, Q2_FC), 3),
  Interpretation = ifelse(c(Q2_III, Q2_FC) > 0, "predictive relevance", "no
predictive relevance")
)
print(Q2_tbl)
```