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Organisational Ambidexterity in the Context of Artificial Intelligence: A Systematic Literature Review on AI’s Impact on Exploration and Exploitation

International Business
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Master's thesis

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Student's statement regarding the use of Artificial Intelligence (AI) for preparing and/or writing this thesis:

☐ **I have not used any AI-based tools.**

☒ **I have used AI-based tools**. Their use is documented in the Appendix 3. The AI tools were used in a way that complies with academic integrity guidelines.

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Abstract

Existing research highlights that artificial intelligence (AI) technologies impact organisational ambidexterity. Yet, the literature offers fragmented viewpoints, as the studies are scattered across various ambidexterity focus areas, industries, and geographies. This creates a significant gap in the understanding of how AI influences exploration and exploitation on an organisational level. The main research aim of this thesis was to synthesise a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation.

By following a rigorous and transparent systematic literature review process, this thesis incorporated the findings from 71 peer-reviewed articles. Data analysis adhered to a hybrid approach. First, the thematic analysis was conducted in an inductive manner, uncovering recurring themes and patterns, followed by the application of ambidexterity theory as analytical lens to group the findings into three main domains – AI-enabled exploration, AI-enabled exploitation, and AI-enabled organisational ambidexterity.

As a result, 11 themes were identified. In the exploration domain, it was identified that AI enables exploratory innovation, sensing and seizing of new business opportunities, and creativity. In the exploitation domain, it was discovered that AI enables efficiency gains, improves the efficiency of business functions, enables exploitative innovation, improves decision-making, and acts as a learning assistant. In the organisational ambidexterity domain, it was uncovered that AI aids in balancing exploration and exploitation, as well as enables ambidextrous learning and innovation.

As a final outcome of this thesis, a conceptual framework of AI-driven organisational ambidexterity was developed. The framework incorporates organisational and contextual conditions, AI capabilities, AI-enabled mechanisms of organisational ambidexterity, exploratory activities, exploitative activities, organisational ambidexterity and tensions, and it suggests a conceptual explanation of how these constructs interact. In essence, the framework proposes that conditions and AI capabilities could activate mechanisms that enable both exploratory and exploitative activities, which, in turn, shape organisational ambidexterity. This thesis identified four AI-enabled mechanisms of organisational ambidexterity: innovation and opportunity recognition, optimisation, learning and knowledge management, and cognitive and analytical mechanisms. As an additional layer of realism, the framework highlights inherent tensions that could occur in this process.

Keywords: organisational ambidexterity, exploration, exploitation, AI, artificial intelligence, AI capabilities, AI mechanisms, tensions, conceptual framework, systematic literature review

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1 Introduction

This chapter introduces the background information on organisational ambidexterity and its evolution. It continues with a definition of the research gap and the outline of the research aim and sub-objectives. This chapter concludes with a description of the structure of this thesis.

1.1 Background

We are living in an era of an unprecedented pace of change, particularly in relation to technological advancements. Progress is occurring at such a rapid pace that significant transformations can occur within a short time, and businesses are required to continuously adapt. Technological developments, such as artificial intelligence (AI), have altered the way companies operate. (Yun 2024, 1) This phenomenon represents an environment where change is not an occasional event but a continuous state, challenging traditional organisational structures and processes that were designed for relative stability (Verhoef et al. 2021, 889; Wirtz et al. 2010, 272). These emerging technologies have created a situation for organisations where, on one hand, the new tools offer exceptional opportunities for innovation (Yun 2024, 1). However, on the other hand, the rapid pace of change threatens operational stability and creates adaptation challenges (Verhoef et al. 2021, 889; Wirtz et al. 2010, 272).

This tension between change and stability has been conceptualised into a theory of organisational ambidexterity approximately 50 years ago (cf. Duncan, 1976). Organisational ambidexterity refers to businesses' activities that are simultaneously targeted at creating incremental and discontinuous innovation (Tushman & O'Reilly 1996, 24). March's (1991) seminal research established the foundation for this theory with definitions of exploration and exploitation. Exploration refers to identifying new opportunities and promoting change (March 1991, 71; Lubatkin et al. 2006, 648; Kostopoulos & Bozionelos 2011, 387), while exploitation focuses on refining existing capabilities and ensuring stability (March 1991, 71; Gupta et al. 2006, 693; Kostopoulos & Bozionelos 2011, 387). Maintaining a balance between the two activities is crucial, as excessive focus on either dimension may create negative consequences. Companies that direct their focus only to exploratory activities may create innovations but are likely to struggle to capture their value. In contrast, businesses that fixate on exploitation are at risk of becoming obsolete, sacrificing their competitive advantage. (March 1991, 71) Since its inception, organisational ambidexterity theory has evolved and expanded. One of the most prominent changes is the shift in the view of the theory from dualism to duality where stability and change complement each other rather than constantly compete (Farjoun 2010, 203).

1.2 Research Gap

As the field that has existed for many decades, organisational ambidexterity has been widely researched (March 1991; Tushman & O'Reilly 1996; Raish & Birkinshaw 2008, 375). The existing research includes numerous studies incorporating the broad technological context, such as digitalisation and technological capacity, into organisational ambidexterity (cf. Åkesson et al. 2018, 276; Yunita et al. 2023, 1). These studies have individually advanced our understanding of how firms balance stability and change, yet their findings are scattered across various technologies, industries and cultural contexts, resulting in a fragmented picture (cf. Åkesson et al. 2018; Kassotaki 2022, 1; cf. Yunita et al. 2023).

During the last 10 years, the field researching the impacts of AI on organisational ambidexterity has evolved, since the technology became more widespread and available (LeCun et al. 2015, 436; Makridakis 2017, 47; Dwivedi et al. 2021, 2). These empirical studies enhanced our understanding of the interplay between AI and organisational ambidexterity, for instance, in relation to various AI technologies, such as cognitive computing (Kaur et al., 2019). Additionally, numerous studies highlight the effects on specific business functions, such as supply chain or customer service (Cao et al., 2024; Al-kahtib et al., 2025). Overall, existing research papers represent various focus areas, industries and cultural contexts, as can be observed in Table 1.

Table 1. Examples of existing studies on AI and organisational ambidexterity

Study	Research method	Research focus	Context	Major findings
Kaur et al., 2019	Semi-structured interviews of 20 UAE executives	The function of cognitive computing in global partnerships	Cognitive computing, United Arab Emirates focus	Cognitive computing acts as an enabler of ambidexterity and aids in information access in relation to global partnerships
van de Wetering et al., 2022	Survey of 257 C-level practitioners	Routine vs. innovation use of AI	Europe-focused, impacts of COVID-19	Ambidextrous usage of AI improves businesses' transformation capability
Cao et al., 2024	Case study of customer service businesses	AI used to switch between modes of ambidexterity in customer service businesses	Customer service focus	Successful switch between various ambidexterity modes requires firms to prevail technological, stakeholder and process hurdles

Sliż & Jackowska, 2025	Surveys of 340 large & medium-sized service enterprises	AI implementation maturity	Poland-focused	Ambidexterity is the most crucial determinant linked with AI implementation maturity
Al-kahtib et al., 2025	Surveys of 210 textile manufacturers in Jordan	Effects of organisational ambidexterity on circular supply chains	Supply chain focus, Jordan textile firms focus	Organisational ambidexterity positively impacts circular supply chains

As Table 1 illustrates, prior studies differ significantly along several dimensions. They employ various research methods: from surveys to case studies and interviews. Moreover, each study focuses on specific and often isolated aspect on AI-enabled organisational ambidexterity. Lastly, they differ in contextual settings, including type of technology, geography, and business function. For instance, some studies examine the impacts of AI specifically in the supply chain domain or customer service. As a result, many of the existing studies focus on a selected isolated aspect of organisational ambidexterity in the context of AI, rather than examining how AI shapes exploration and exploitation in an integrated manner. This fragmentation limits the ability to develop a coherent theoretical understanding of how AI simultaneously influences both domains, leaving a significant gap in explaining how AI impacts exploration and exploitation activities within businesses on an organisational level (Farjoun 2010, 220; cf. Haenlein & Kaplan 2019, 9; Jafari-Sadeghi et al. 2021, 100). In other words, the existing literature lacks a comprehensive overview that captures what is known about organisational ambidexterity in the context of artificial intelligence. There is a need to assemble the existing puzzle pieces together to reveal a bigger picture. This is particularly relevant at the present time as the pace of technological evolution continues to accelerate, creating new organisational challenges (Verhoef et al. 2021, 889; Wirtz et al. 2010, 272).

1.3 Research Aim

This thesis addresses the above gap by conducting a systematic literature review to examine the link between artificial intelligence and organisational ambidexterity. The balance between exploration and exploitation in a given environment is a highly complex subject and no single study is able to provide comprehensive results. A systematic literature review caters particularly well to this topic, allowing for an analysis of all relevant articles and a synthesis of the insights into a single framework.

The main research aim is to synthesise a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation. In order to achieve this aim, this research includes two sub-objectives:

1. To synthesise insights on how artificial intelligence impacts exploration
2. To synthesise insights on how artificial intelligence impacts exploitation

1.4 Structure of the Thesis

This thesis is structured in the following way. The first chapter outlines the background of the study, research gap and research aim. The second chapter defines organisational ambidexterity and explains the evolution that the field has undergone over the last decades. Additionally, important components of artificial intelligence are explained. This chapter lays the theoretical foundation of the two areas of focus to enhance the reader's understanding of the subjects. However, the link between organisational ambidexterity and artificial intelligence is not described in detail in this chapter, as this is the main focus of Chapter 4. Chapter 2 concludes with a high-level theoretical synthesis.

Chapter 3 describes how the systematic literature review approach is utilised in this thesis, including data collection, data analysis and evaluation of the study. Chapter 4 presents the main findings of the thesis and concludes with a framework of AI-enabled organisational ambidexterity. Chapter 5 highlights the theoretical contributions of the study, practical implications, as well as limitations and future research suggestions. Lastly, Chapter 6 presents a summary of this thesis.

2 Theoretical Underpinnings of Organisational Ambidexterity and Artificial Intelligence

This chapter expands on the existing research on organisational ambidexterity, the evolution of the field and its components. It continues by providing definitions and explanations of artificial intelligence. It concludes with the synthesis of the theory.

2.1 Organisational Ambidexterity

2.1.1 Definitions and Core Concepts of Organisational Ambidexterity

Organisational ambidexterity is a pivotal concept in management theory, first introduced by Duncan (1976, 184), highlighting that organisations need certain structures to allow for activities aimed at innovation to be integrated into existing business activities. It has been defined in various, but closely related, ways (cf. Tushman & O'Reilly 1996; cf. Gibson & Birkinshaw 2004; cf. Lubatkin et al. 2006; cf. Brix 2019). Table 2 provides some of the definitions:

Table 2. Definitions of organisational ambidexterity

Definition	Source
"The ability to simultaneously pursue both incremental and discontinuous innovation and change…"	Tushman & O'Reilly 1996, 24
"...the capacity to simultaneously achieve alignment and adaptability at a business-unit level"	Gibson & Birkinshaw 2004, 209
"Ambidextrous firms are capable of exploiting existing competencies as well as exploring new opportunities with equal dexterity"	Lubatkin et al. 2006, 647
"Ambidexterity refers to the ability to simultaneously pursue two things, such as exploration and exploitation, efficiency and flexibility, or alignment and adaptability"	Zhang et al. 2016, 132
"Organisational ambidexterity is a construct that refers to firms that are able to both explore new opportunities and exploit existing knowledge"	Brix 2019, 339

A noticeable similarity in these definitions is the inclusion or implication of the word "simultaneously", which highlights the essence of organisational ambidexterity. For the purposes of this thesis, the definition by Tushman and O'Reilly (1996, 24) is adopted. This definition is chosen because it directly addresses the tension between managing incremental and discontinuous, or in other words exploitative and exploratory, innovation, which is a central issue in this research. Furthermore, this definition is widely accepted and cited in the academic literature (Raisch & Birkinshaw 2008, 375; Birkinshaw & Gupta 2013, 288; Junni et al. 2013, 299; Castaño-Martínez et al. 2020, 2410). By applying this definition, this study can explore the dual requirements for exploration and exploitation in technology-driven environments.

Exploration and exploitation are the key terms of the organisational ambidexterity theory (March 1991, 71; Gupta et al. 2006, 693; Mom et al. 2007, 910). Exploration refers to organisational activities, such as taking risks, exploring new opportunities and driving innovation (March 1991, 71; Lubatkin et al. 2006, 648; Kostopoulos & Bozionelos 2011, 387). Furthermore, exploration includes learning activities, for instance, pursuit of novel insights (Gupta et al. 2006, 693). Overall, exploration aims to react to the current environmental trends, as well as create new ones, by developing innovative technologies and markets (Lubatkin et al. 2006, 648).

In contrast, exploitation focuses on refining existing processes and enhancing efficiency (March 1991, 71; Gupta et al. 2006, 693; Kostopoulos & Bozionelos 2011, 387). Exploitation activities often utilise existing knowledge by internalising it and refining it to introduce incremental improvements. Essentially, exploitation aims to react to present environmental conditions by adjusting current technologies. (Lubatkin et al. 2006, 648)

As is evident from the descriptions above, both exploration and exploitation are affiliated with learning and innovation, however, of various kinds. One of the ways to draw a distinction between exploration and exploitation is by understanding which learning and innovation ways they follow. (Gupta et al. 2006, 694) In the exploration domain, learning is achieved through deliberate experimentation (Levinthal & March 1993, 105; Gupta et al. 2006, 694; Mom et al. 2007, 912). Exploratory learning involves searching, brainstorming and cultivating novel ideas and capabilities (Kostopoulos & Bozionelos 2011, 389). In the exploitation domain, learning includes refinement activities and reuse of existing knowledge (Levinthal & March 1993, 105; Gupta et al. 2006, 694; Kostopoulos & Bozionelos 2011, 387). In short, exploration develops novel knowledge, while exploitation extends existing knowledge (Kostopoulos & Bozionelos 2011, 389). Businesses tend to select one or the other type of learning for a given task, depending on the needs of particular organisational units and the complexity of the task (Brix 2019, 342). If a firm solely focuses on exploratory learning, it is likely to face a drawback of not being able to realise or benefit from the knowledge it develops. Equivalently, if a firm relies solely on exploitative learning, it risks becoming obsolete over time. Longevity and success of a firm are dependent on achieving a balance between the two types of learning. (Levinthal & March 1993, 105; Prieto-Pastor & Martin-Perez 2015, 591)

Regarding innovation, it could be described as a complicated and dynamic process of creating innovation capabilities through exploration of novel resources and exploitation of novel blends of resources. In turn, ambidextrous innovation is a business's ability to simultaneously flourish both explorative and exploitative capabilities for exploratory and exploitative innovation. (Zhang et al. 2016, 132) Explorative innovation refers to innovations created with a purpose of accessing new product-market domains (Jansen et al. 2005, 352; Gupta et al. 2006, 694). Such innovation requires businesses to obtain, cultivate and apply novel technological skills and resources (Zhang et al. 2016, 132). Exploitative innovation, on the other hand, refers to improvements in current processes, expanding the existing technological trajectory (Jansen et al. 2005, 352; Gupta et al. 2006, 694). Thus, exploitative innovation allows for continuous advancements in the innovation process (Zhang et al. 2016, 132).

Some research compares exploration and exploitation to radical and incremental organisational change. Definitions of radical and incremental innovation are similar to the previously presented definitions of exploratory and exploitative innovation. Radical innovation "…fundamentally changes the technological trajectory and associated organisational competencies" (Benner & Tushman 2003, 243), while incremental innovation involves minor changes to the technological trajectory. (Benner & Tushman 2003, 243)

In its essence, exploratory organisational activities refer to the creation of new knowledge and novel innovations. While exploitative activities aim at reusing existing knowledge and extending current innovations. (Gupta et al. 2006, 694) It is important to note the inherent complexity related to balancing exploration and exploitation. Companies that prioritise exploration while neglecting exploitation may continuously foster innovation, however, they may struggle to develop the ideas into valuable assets. On the contrary, an excessive focus on exploitation can lead to reduction of learning and gaining novel competencies, which could result in stagnation. Achieving a balance between exploration and exploitation is crucial, as it enables organisations to reap the benefits of innovation while maintaining stable operational efficiency, which ultimately supports the long-term success of a company. (March 1991, 71; Simsek et al. 2009, 867; Kostopoulos & Bozionelos 2011, 387; Brix 2019, 337) The tension between these two activities and how to balance them has been the main academic discourse in the field of ambidexterity (March 1991, 71; Raisch et al. 2009, 685; Lubatkin et al. 2006, 648; Smith et al. 2017, 304). The complexity of the subjects shows in the lack of academic consensus over how this balance can be achieved in practice (Prieto-Pastor & Martin-Perez 2015, 318).

2.1.2 Evolution of Organisational Ambidexterity

The ambidexterity theory has undergone evolution since its introduction. Early research presented exploration and exploitation as a dualism, where these two activities are in a state of competition (March 1991, 71; Raisch et al. 2009, 685). The development of the theory continued with Tushman and O'Reilly's (1996) work, where they incorporate the previous knowledge and define a theory of organisational ambidexterity. They argue that to achieve long-term success, businesses must enable incremental and radical change (Tushman & O'Reilly 1996, 8).

The beginning of the twenty-first century experienced a large increase in interest in organisational ambidexterity. In 2004, there were fewer than 10 journal articles related to this topic, whereas in 2009, more than 80 articles were published. This surge resulted in a continued and more nuanced development of the field. (Raisch et al. 2009, 685) For instance, a meta-analysis of the empirical studies suggests a strong positive relationship between ambidexterity and organisational performance. This study highlights that the balance between exploration and exploitation is dependent on the right fit with organisational context and environment. (Junni et al. 2013, 310)

Another important advancement of the field is the introduction of contextual ambidexterity, which refers to a company's ability to balance two seemingly opposing goals, such as being in alignment with current business objectives while also adjusting to changes in the external environment (Gibson & Birkinshaw 2004, 209). In other words, contextual ambidexterity relies on the organisation's environment to enable both exploration and exploitation within the same business unit or team. In contrast, structural ambidexterity involves separating the business units or teams into one being focused on exploration and another on exploitation. As a result, these units are often physically or structurally separated to manage conflicting demands. (Raisch & Birkinshaw 2008, 397)

More recent works challenge the original view of ambidexterity. Farjoun (2010, 203) bases their research on March's (1991) paper and translates the terms of exploration and exploitation into change and stability. Farjoun (2010, 203) argues that March (1991) presents change and stability as a dualism, where these two states are mutually exclusive. An alternative view is proposed, where stability and change are viewed as a duality, indicating that these two states complement and enable each other. (Farjoun 2010, 203)

Academic scholars also address the practical aspects of the theory. O'Reilly and Tushman (2011, 18) further expand the ambidexterity theory by defining actions that managers could execute to realise an ambidextrous strategy. They suggest business leaders to define a vision and identity, encourage team leaders to engage in both exploration and exploitation activities, establish separate teams to prioritise just one of the two activities and create units that are capable of helping with resource allocations and conflicts (O'Reilly & Tushman 2011, 18).

Organisational ambidexterity theory is sometimes used in association with dynamic capabilities theory (Benner & Tushman 2003, 248; Zhang et al. 2016, 132; Fu et al. 2020, 3), which offers another view of how organisations can achieve sustainable performance in volatile contexts. Teece (2007, 1319) investigates how organisations can use their internal and external resources to respond to rapidly changing environments and defines dynamic capabilities as the "firm's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments" (Teece et al. 1997, 516). The study defines the microfoundations of dynamic capabilities, including sensing opportunities, seizing them through strategic actions and transforming the companies to maintain competitiveness (Teece 2007, 1322-1326). Ambidexterity has been shown as a form of dynamic capability (Zhang et al. 2016, 132). The dynamic capability perspective of organisational ambidexterity could highlight the processes that enable business to "reconfigure existing organisational assets and competencies in a repeatable way to adapt to changing circumstances…" and "orchestrate the complex trade-offs that ambidexterity requires" (O'Reilly & Tushman 2008, 200).

Taken together, the organisational ambidexterity theory, first introduced more than 45 years ago, has since evolved and expanded. Different scholars propose various definitions, contexts and conceptual viewpoints. This theory addresses complex organisational dilemmas and continues to evoke research interest.

2.1.3 Typology of Organisational Ambidexterity

As it was earlier indicated, balancing exploration and exploitation is not a trivial task. As a result, several typologies of ambidexterity have emerged with the purpose of answering how to balance these competing requirements. These typologies show how companies can organise internal workflows to balance ambidexterity. (Kassotaki 2022, 2) The typology is presented in Figure 1.

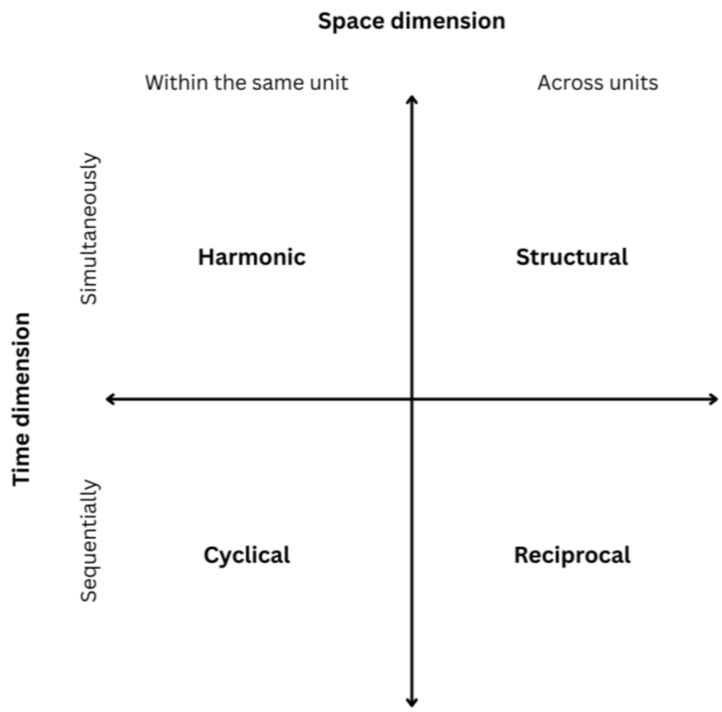

Figure 1. A typology of organisational ambidexterity (adapted from Kassotaki 2022, 5)

As Figure 1 illustrates, there are four most common typologies of ambidexterity. Time dimension indicates whether ambidextrous activities are implemented simultaneously or sequentially over time. Space dimension showcases the internal structure of organisations – whether ambidextrous activities occur within one independent unit or several interdependent. (Kassotaki 2022, 5)

The first typology is *contextual*. It suggests conducting exploration and exploitation tasks simultaneously within the same business department (Simsek et al. 2009, 869; Kassotaki 2022, 3). Contextual ambidexterity involves establishing internal processes for employees to make decisions on how to split their resources between competing demands (Gibson & Birkinshaw 2004, 209; Huang & Kim 2013, 925). The positive sides of this approach include potential for creating competitive advantage, as such form of ambidexterity is difficult to imitate, stakeholder satisfaction and increased manager performance. On the downside, it is expensive to build. This typology could be relevant for corporate venture units, which are built to exchange new insights quickly – a capability essential for simultaneous pursuit of new innovations and applicable solutions. (Kassotaki 2022, 6)

The second typology is *structural* ambidexterity, which advocates for businesses to simultaneously divide explorative and exploitative tasks into two separate units (Kassotaki 2022, 3). The main purpose is to enable businesses to address competing demands of exploration and exploitation (Gibson & Birkinshaw 2004, 211; Huang & Kim 2013, 925). The key distinction of this typology from the previous is the interdependent nature of it. Each business group is implementing its own actions and possesses its own leadership team, culture and control systems. (Simsek et al. 2009, 884) This typology could lead to enhanced innovation and high financial returns. However, the key challenge is the combination of explorative and exploitative results across separate units. This could be solved through establishment of a common vision, effective team coordination and knowledge management systems. This approach is often used in finance sector or businesses with strategic alliances. (Kassotaki 2022, 6)

The third typology is *cyclical* ambidexterity. It suggests the same business unit to alternate between explorative and exploitative periods (Kassotaki 2022, 3; Cantarello et al. 2012, 34). In essence, firms endure long phases of exploitation, mixed with short periods of exploration (Simsek et al. 2009, 882). In practice, it could mean that a company first innovates and afterwards switches focus towards exploitation to commercialise that innovation. This typology often results in enhanced innovative performance. In order to achieve this, businesses need to establish clean systems for navigating conflicts when the requirements in structure, routines and resource allocation switch between exploration and exploitation. This typology is often adopted by organisations focusing on research and development, such as biotechnology or software businesses. (Ardito et al. 2021, 370; Kassotaki 2022, 6)

The fourth typology is *reciprocal* ambidexterity, which entails subsequent ambidextrous activities across different business units. In this form, the results of exploratory activities from one unit act as input for exploitation for another unit. (Simsek et al. 2009, 886; Kassotaki 2022, 3) This typology is often implemented in inter-organisational environments between strategic partners. These partners could form strategic alliances to navigate complex environments, such as international markets. To succeed, the partners need to develop working solutions for knowledge exchange, collaboration, joint decision-making and resource distribution. (Simsek et al. 2009, 887; Kassotaki 2022, 6)

As with the majority of organisational theories, the reality of the business world proves to be more complex. Hence, these four typologies are not meant to be perceived in a rigid way. Companies often engage in hybrid strategies of organisational ambidexterity, depending on their needs and context. (Kassotaki 2022, 6)

2.2 Artificial Intelligence

2.2.1 Definitions and Classification of Artificial Intelligence

Technology, which could be understood as a set of knowledge parts, expertise, methods, processes and experiences within a problem-solving activity (Harwood & Eaves 2020, 2), has been rapidly evolving since the beginning of the 2000s, impacting the way businesses operate. Companies need to effectively navigate this evolving environment and adapt to the technological changes to remain competitive. (Verhoef et al. 2021, 889; Wirtz et al. 2010, 272) The emerging technologies encompass a wide range of developments. The SMACIT acronym could be used to describe the different types of digital technologies. It includes social, mobile, analytics, cloud and the internet of things (IoT) technologies. (Vial 2019, 122) The main focus of this thesis is on technological advancements that are rapid and continuous in nature, which distinguishes them from more gradual technological developments. Rapid continuous change, such as artificial intelligence, could be described as a disturbance in a company's competitive landscape (Vial 2019, 133). This continuous change forces businesses to integrate processes that facilitate continuous adaptation in order to maintain their competitive advantages (Vial 2019, 133).

Technological advancements can differ in their intensity and impact. These developments can be incremental, which usually means that the progress occurs at a slow pace. For instance, continuous small improvements that develop or extend the existing technology would be considered incremental. Such advancements can enhance the efficiency of a given technology without fundamentally altering it. In contrast, some technological developments can be categorised as a radical innovation. It could involve launching a new product or significantly improving an existing technology. Such technologies could reshape the industry and inspire serious market shifts. (Tushman & Anderson 1986, 441; Vial 2019, 133) Recognising these differences is important for understanding how organisations respond through exploration and exploitation (cf. Raisch & Birkinshaw 2008, 377).

A particular emphasis in this thesis is placed on artificial intelligence (AI), as these developments impact organisations in a significant way. Even though this is a novel area in the academic literature, since this subject has only emerged in the last decade, it attracts research interest (Jafari-Sadeghi et al. 2021, 100; Haenlein & Kaplan 2019, 9).

Artificial intelligence can be defined as a tool that can perform cognitive functions that resemble human activities, such as learning, understanding speech and problem solving (Russell & Norvig 2021, 2). Artificial intelligence can also be described more thoroughly as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Haenlein & Kaplan 2019, 5). The essence of both definitions is the evolving ability of computers to execute similar tasks to those accomplished by the people (Dwivedi et al. 2021, 2). According to the category of intelligence used, such as cognitive, emotional or social, AI can be categorised as analytical, human-inspired or humanised respectively. Another classification is dividing artificial intelligence into Narrow, General, and Super Intelligence. (Haenlein & Kaplan 2019, 6)

Narrow artificial intelligence represents the technology that we currently possess. This technology has been created to execute specific tasks. The current models already possess certain qualities that exceed what humans are able to perform, such as recognising patterns. However, they are nowhere near the level of human intelligence, since they lack certain skills, such as complex reasoning and consciousness. This implies that narrow AI can support people in performing complicated tasks, however, it does not represent everything that humans can accomplish. (Haenlein & Kaplan 2019, 6; Triguero et al. 2024, 1-2)

A technology that is far superior to the narrow AI is artificial general intelligence. Artificial general intelligence is a system that is capable of thinking on its own, possessing the same capabilities as humans or even exceeding them. Achieving this level of AI has been an aspiration of scientists for many years. (Haenlein & Kaplan 2019, 6; Triguero et al. 2024, 1) Another important term is generative artificial intelligence. Generative artificial intelligence is different from artificial general intelligence. (Triguero et al. 2024, 2) This technology is able to produce complex data based on its vast training set. Due to the reinforcement learning contexts, the system is capable of learning from broad and flexible scenarios. (Triguero et al. 2024, 8)

2.2.2 Evolution of Artificial Intelligence

The origins of Artificial Intelligence date back to the 1940s, with the term and basic technology existing for many decades. The development of AI has undergone several phases of progress and setbacks. (Haenlein & Kaplan 2019, 5)

The execution of artificial intelligence requires two components: an artifact and the intelligence itself. The computer has been selected to represent the artifact. The invention of the computer, which happened during the World War II, laid the foundation for artificial intelligence. (Russell & Norvig 2021, 14) The first operational computer, called The Bombe, was designed by Turing in 1940 strictly for the warfare purposes (Haenlein & Kaplan 2019, 6). Turing’s machine was able to decipher the

German Enigma code, which was considered to be an impossible task for the human mind. This invention led Turing to wonder what else is possible to achieve with this technology. As a result, he created a test called the Turing Test, which up until this day is utilised to test the intelligence of an artificial system. (Haenlein & Kaplan 2019, 7)

This field experienced a steady influx of innovation resulting in each new generation of machines doubling its performance every 18 months (Russell & Norvig 2021, 14). The term "artificial intelligence" was introduced in 1956 by Minsky and McCarthy, who led a program in Dartmouth College named "Dartmouth Summer Research Project on Artificial Intelligence". This program is considered the beginning of the AI development. (Haenlein & Kaplan 2019, 7)

Following this workshop, the artificial intelligence area experienced almost 20 years of growth. One of the most prominent inventions of that period is the ELIZA program, designed by Weizenbaum between 1964 and 1966. This program used natural language processing to talk with humans and was one of the first tools that passed the Turing Test. (Haenlein & Kaplan 2019, 7)

During these fast progress years, in 1970, Minsky estimated that it is possible to build a computer with the same level of intelligence as an average human within three to eight years. However, soon after that both US and British governments paused high spending on AI research and development, which significantly hindered the pace of progress. (Haenlein & Kaplan 2019, 7)

One of the issues with early AI was its focus on building "Expert Systems" (Haenlein & Kaplan 2019, 8). These systems are a "collection of rules which assume that human intelligence can be formalised and reconstructed in a top-down approach as a series of "if-then" statements" (Haenlein & Kaplan 2019, 8). Yet, in reality, this assumption proved to be too inflexible. In order to perform the tasks that humans aspired for, a system requires to understand the broader context of the data it is given, learn from it and use its insights accordingly. This realisation resulted in the research field of artificial neural networks. However, in the 1970s machines did not possess the necessary processing power to execute such tasks. This field experienced progress 45 years later with the development of deep learning technology. Currently artificial neural networks and deep learning represent an integral part of modern AI and are the core aspect of image and speech recognition. (Haenlein & Kaplan 2019, 8)

Followed by years of slow progress, recent developments in big data and computing power have revived AI, making it an integral part of day-to-day life (Haenlein & Kaplan 2019, 9). With the adoption of the Internet across the globe in the 1990s, AI technologies have undergone a new way of development, becoming widespread. Additionally, AI tools act as an essential part of various Internet services, including search engines and recommender systems. (Russell & Norvig 2021, 27)

One of the most prominent recent breakthroughs in technology was the public release of the ChatGPT program, created by OpenAI in collaboration with Microsoft (Triguero et al. 2024, 10). OpenAI is a research and deployment organisation with a vision of developing artificial general intelligence (OpenAI, 2026). In 2022, OpenAI released its GPT-4 model, which delivered unprecedented capabilities (Triguero et al. 2024, 10). GPT stands for generative pretrained transformer (Zhang & Shao 2024, 2062). This technology was developed using two stages. First, the model was trained using a vast amounts of text. Second, reinforcement learning technique was utilised, which includes a human input into the training process. As a result, GPT-4 can write text almost like a human. (Triguero et al. 2024, 10), engage in discussions with users and fulfil their inquiries (Zhang & Shao 2024, 2062). A similar popular tool, which also uses large language models to produce text, is Microsoft 365 Copilot (Callari & Puppione 2025, 5002).

Overall, the development of artificial intelligence has progressed from early rule-based expert systems to data-driven networks and, most recently, to large-scale generative models such as GPT-4. This trajectory reflects a gradual shift from relatively inflexible models towards the systems that can learn patterns from vast volumes of data. Tools, such as ChatGPT and Microsoft Copilot, exemplify the new generation of AI, as they embed complex technologies into everyday applications. This makes AI widely accessible to organisations and employees. The following chapter provides an overview of various technologies that form artificial intelligence.

2.2.3 Core Artificial Intelligence Technologies

The term artificial intelligence encompasses multiple tools that are needed to perform the tasks. These tools include natural language processing capabilities, knowledge representation, automated reasoning, and machine learning (Russell & Norvig 2021, 2-3). Natural language processing refers to the ability of a computer to understand human language and communicate back (Hurwitz et al. 2015, 17; Russell & Norvig 2021, 2-3). Knowledge representation refers to the capability of a machine to save the information it receives. Automated reasoning connects to the previous tool, by actively using the saved information to process new enquiries and propose solutions. Finally, machine learning is a complex technology aiming to adapt to novel situations and learn new patterns. Additionally, computer vision and robotics are required for AI performing physical tasks. Computer vision allows to view the physical objects and robotics aid in moving these objects in space. (Russell & Norvig 2021, 2-3)

Modern AI systems are trained on vast amounts of data, which allows them to perform pre-trained tasks well and possibly handle new ones. One important technology that has recently experienced rapid progress is the Large Language Models (LLMs). This technology is connected to natural language processing in a way that it includes training from a large variety of text-based sources, such as books, articles, and websites. This comprehensive learning process allows the AI systems to understand details of language, such as grammar and semantics. As a result, the LLM is capable of creating meaningful and relevant text. This process, that allows the LLMs to train, is called deep learning. (Triguero et al. 2024, 9)

Another important term to define is cognitive computing. Cognitive computing refers to systems designed for human-machine collaboration, where machines assist people in understanding and reasoning complex problems. This technology is capable of analysing both structured and unstructured data in a specific context. Cognitive computing operates with three key principles. The first principle is related to learning – the system learns from the various types of data. Secondly, in order to learn effectively, the system develops models with the context in mind. Thirdly, the system generates hypotheses with the purpose of testing its knowledge to train and refine its capabilities further. (Hurwitz et al. 2015, 13) A term closely related to cognitive computing is big data analytics. It refers to an organisation's ability to manage vast amounts of structure and unstructured data to enable insightful analysis. (Hurwitz et al. 2015, 63)

2.3 Theoretical Synthesis

Organisational ambidexterity does not occur in isolation. The previous research shows that it is impacted by various internal organisational factors, as well as external factors. These factors influence organisational ambidexterity, which in turn, influences performance metrics of a company. (Kassotaki 2022, 2) The interaction between internal and external factors is illustrated in Figure 2.

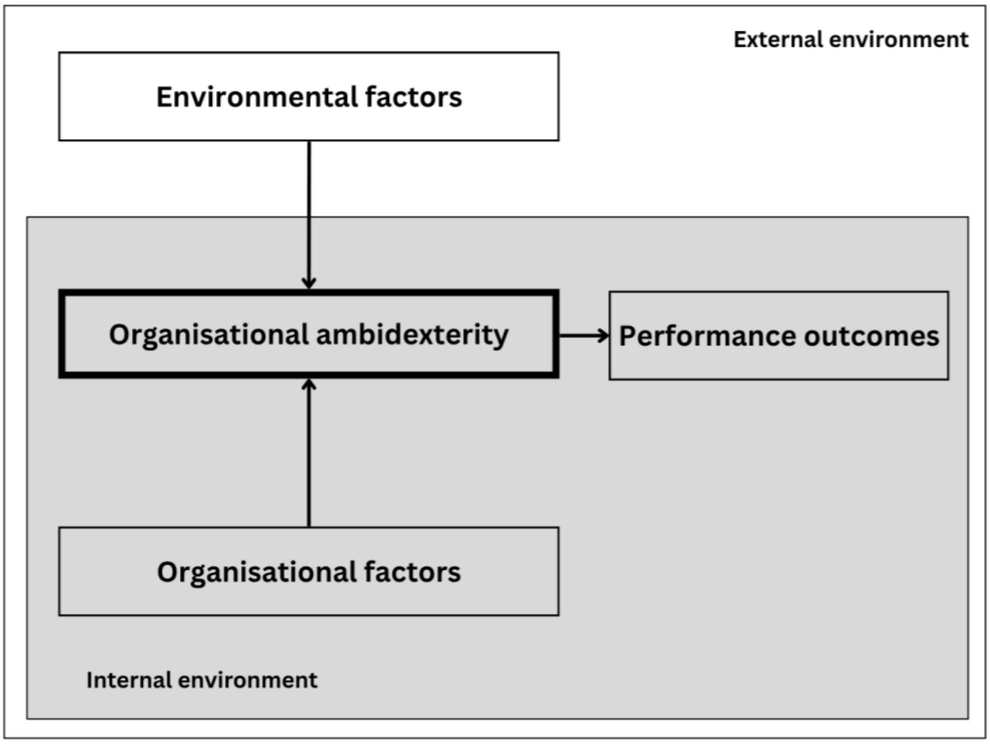

Figure 2. A framework of organisational ambidexterity (adapted from Kassotaki 2022, 4)

Research has demonstrated that organisational ambidexterity exemplifies the best performance in dynamic environments. It could be explained by the fact that dynamic markets force companies to continuously innovate, while increasing efficiency of processes and operations at the same time, since the competitive advantage is continuously challenged. (Kassotaki 2022, 2) Artificial intelligence represents a rapid and disruptive technology, affecting many industries and companies (Jafari-Sadeghi et al. 2021, 100; cf. Haenlein & Kaplan 2019, 9). In essence, AI could create dynamic markets. Drawing on the perspective presented in Figure 2, AI can be viewed as both an internal and external factor. Internally, it is developed and deployed within organisations, shaping processes and capabilities. Externally, it acts as a broader technological force influencing market conditions and stakeholder expectations. Understanding how AI shapes organisational ambidexterity, and how firms can balance exploration and exploitation in this context, represents a critical challenge in today's world (Jafari-Sadeghi et al. 2021, 100; cf. Haenlein & Kaplan 2019, 9). To indicate the boundaries and focus of this thesis, a theoretical synthesis is presented in Figure 3.

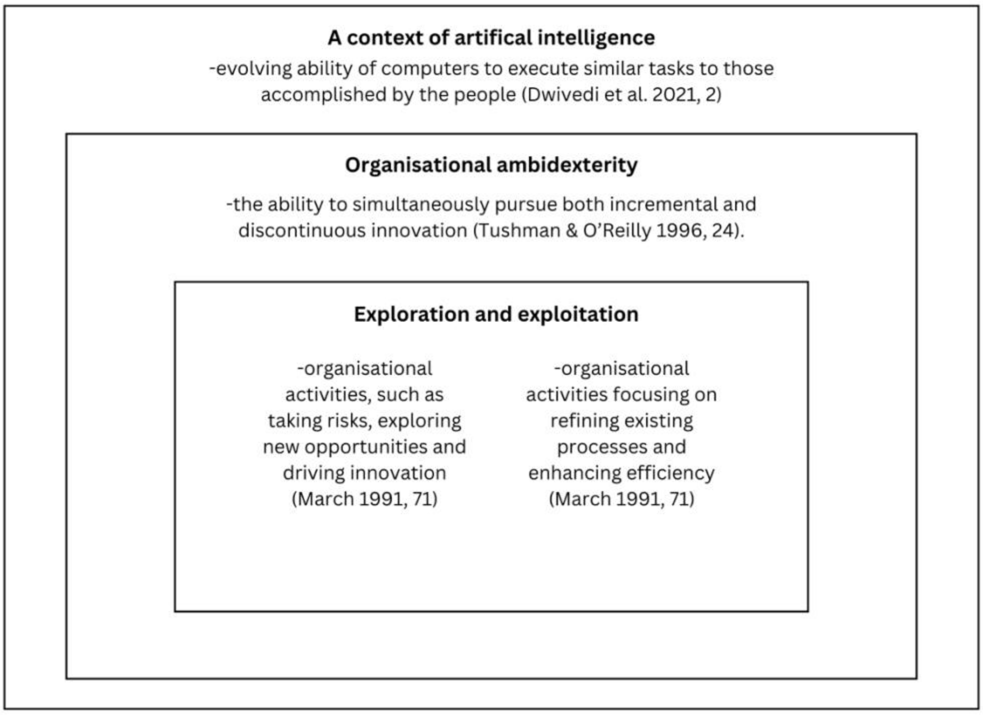

Figure 3. Initial theoretical synthesis

This thesis combines artificial intelligence and organisational ambidexterity to synthesise a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation. Artificial intelligence forms the context of this research and acts as the outer layer of the theoretical framework. Within this environment, organisational ambidexterity provides a lens to evaluate how companies balance innovation with operational efficiency. At the core of the framework are two ambidexterity processes: exploration and exploitation, providing the analytical focus of this research.

The initial theoretical framework is intentionally high-level as it provides conceptual guidance for the systematic literature review, while remaining open to refinement and iteration. Chapter 4 presents a richer, data-informed framework created through the synthesis of the findings.

3 Research Design

This study follows a systematic literature review approach. First, this approach is described and the reasons for selecting it are highlighted. Second, the data collection and data analysis activities are documented to showcase how the findings were synthesised. Third, the quality of the research is discussed.

3.1 Research Approach

A systematic literature review is a research approach that adheres to a systematic, transparent and replicable way of determining relevant academic literature regarding a specific topic (Fisch & Joern 2018, 103). This methodology is suitable for investigating a large pool of knowledge for a specific purpose as it allows to analyse the existing literature and evolve it further. Given the systematic nature of this approach, it is considered to result in high-quality outcomes. (Tranfield et al. 2003, 208-210)

The selection of this method needs to be justified, for instance, through the appropriate research questions (Fisch & Joern 2018, 104). Overall, the field of ambidexterity is well-researched, however, it lacks a conceptual framework of how artificial intelligence shapes it. (Farjoun 2010, 220; cf. Haenlein & Kaplan 2019, 9; Jafari-Sadeghi et al. 2021, 100). This study addresses this gap by systematically reviewing existing research to develop the missing conceptual framework.

The main goal of the systematic literature review research is to deduce meaningful conclusions. Even though the name of the approach may suggest the idea that such studies only provide descriptive summaries of existing research, this method expands beyond that. An excellent literature review must include a comprehensive summary of the studies and, in addition, it must interpret the existing knowledge and synthesise new conclusions. (Fisch & Joern 2018, 105) The main question that a literature review study should answer is: "What do we learn from this summary?" (Fisch & Joern 2018, 105). This could be achieved by developing implications, highlighting research gaps, and presenting suggestions for future research. (Fisch & Joern 2018, 105) As a result of a systematic literature review, this thesis aims to contribute to the field by creating a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation. This systematic literature review followed a three-stage process illustrated in Figure 4 (Tranfield et al. 2003, 214-219).

Figure 4. Methodological process of systematic literature review (adapted from Tranfield et al. 2003, 214)

The first stage was dedicated to planning the research. The activities included clarifying the research problem and the need for research and conducting a scoping study. The second stage involved activities related to conducting the study, including determining the main search terms and strings, as well as evaluation and exclusion criteria. The third stage was related to reporting processes. Reporting entailed two steps. Starting with creating a description of the studies, including information about the authors and the field, and then transitioning to a thematic analysis. (cf. Tranfield et al. 2003, 214-219)

3.2 Data Collection

3.2.1 Systematic Literature Review Search Strategy

A key aspect of a systematic literature review is its replicable and transparent nature. This implies that researchers are required to explain their search strategy in detail regarding the databases, search terms and exclusion criteria. (Tranfield et al. 2003, 215-216; Fisch & Joern 2018, 104)

To increase transparency, selected databases should be disclosed (Fisch & Joern 2018, 104). This thesis utilised two databases to search for academic articles - Scopus and Web of Science. Scopus database is among the world's largest databases, trusted by academics (Elsevier, 2025). Similar to Scopus, Web of Science is a trusted database with over 34,000 search content (Clarivate, 2026). The selection of these databases is particularly suitable for this thesis, as the topic of organisational ambidexterity and artificial intelligence spans across multiple fields, including management and information systems. By utilising both databases, the search query resulted in the necessary saturation given the novelty of the field (cf. Fisch & Joern 2018, 104-105).

As outlined by Tranfield et al. (2003, 214), literature reviews involve implementing scoping studies, which aid in refining the focus area and evaluating the literature. The scoping study executed for this research included performing search queries to obtain an overview of the given field. The initial search strategy focused on conducting two separate searches for exploration and exploitation. Additionally, the initial research strategy included a broader focus on all technological advancements, not limited to AI. The search string included a combination of two key terms: technological advancements and exploration or exploitation. In regard to the search terms for the technology side, terms such as “technological advancements”, “digital transformation” and “emerging technologies” were used. For the exploration side, terms such as “exploration”, “opportunity discovery” and “innovation” were included. The trial search was conducted in Scopus and after limiting the results to the business area, document type being an article and the language of the paper being English, the results revealed 6, 238 documents. A similar search strategy was used for the exploitation topic, resulting in 531 articles. This scoping study showcased that a selected search strategy was too broad, leading to an unmanageable number of articles, most of which were irrelevant.

As the process of conducting a literature review is iterative (Tranfield et al. 2003, 214), further refinement of the search terms was performed. First, the scope of the study was limited to include only artificial intelligence technology instead of the broad term “technological advancements”. This way, the research maintains a clear focus, delivering more concrete conclusions. Second, organisational ambidexterity focus has been further refined. The search strings specify that terms “organisational ambidexterity” and “ambidexterity” can be sourced from title, abstract and keywords, since these terms are specific. However, terms related to exploration and exploitation were limited to the title search only, since they could carry other meanings as well. This way, more relevant search results were achieved.

To contribute to the reproducible nature of a systematic literature review, search terms and keywords that were utilised to discover the literature need to be discussed (Fisch & Joern 2018, 104; Tranfield et al. 2003, 215). This thesis used the search terms presented in Figure 5.

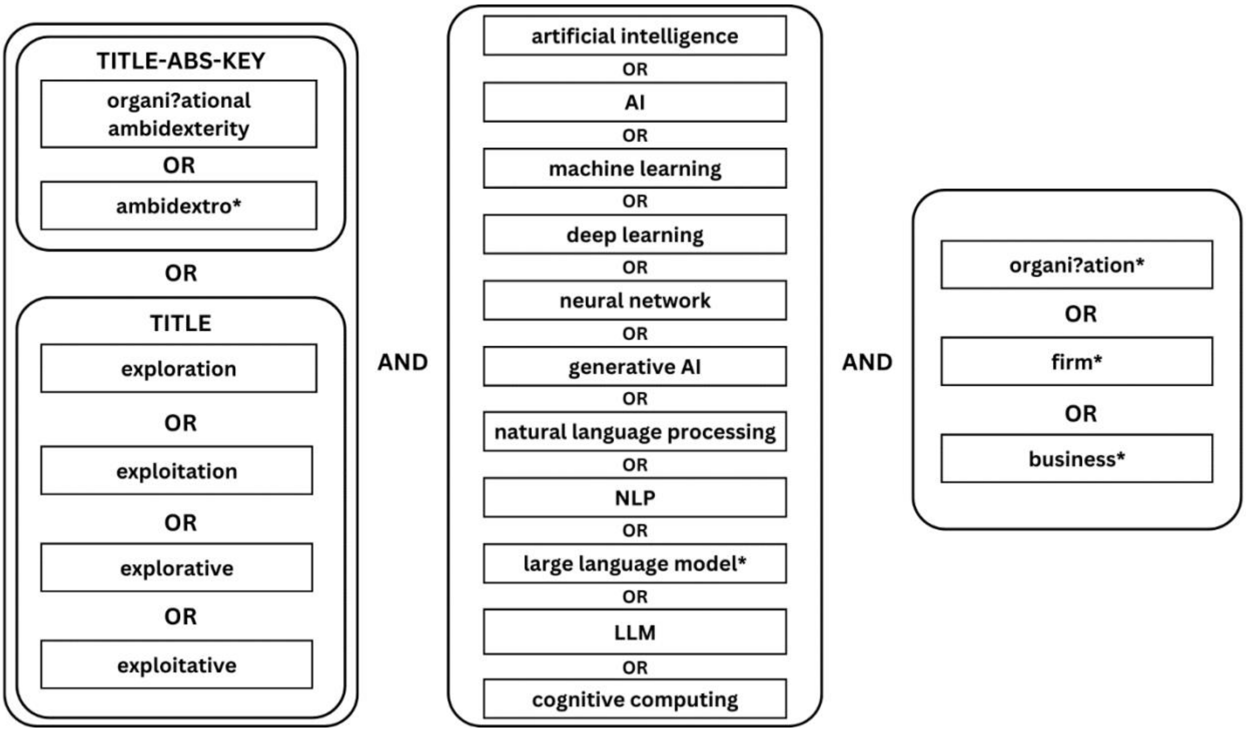

Figure 5. Search terms used for the literature review

A Boolean search strategy was used to identify relevant literature systematically. The search query consists of three main categories. The first category is organisational ambidexterity concepts, such as “organi?ational ambidexterity”, “ambidextro*, “exploration”, “exploitation”, “explorative” and “exploitative”. This category outlines one of the two main research areas.

The second category focuses on the artificial intelligence angle with search terms such as “artificial intelligence”, “AI”, “machine learning”, “deep learning”, “neural network”, “generative AI”, “natural language processing”, “NLP”, “large language model*”, “LLM” and “cognitive computing”. These terms are often used to describe artificial intelligence technologies.

The third category consists of search terms such as “organi?ation*”, “firm*” and “business*. By including these terms, the aim is to enhance the focus on managerial and strategic implications of the papers.

The “OR” operator was used within each category to capture a broad range of relevant studies, while the “AND” operator was utilised to ensure that selected articles address both artificial intelligence and organisational ambidexterity. The search was implemented within the article title, abstract and keywords, except for the group of terms “exploration”, “exploitation”, “explorative” and “exploitative”, which were searched only among title, since the terms can be used in different meanings.

The full Boolean search string utilised for this research in Scopus is the following: (TITLE-ABS-KEY("organi?ational ambidexterity" OR "ambidextro*") OR TITLE("exploration" OR "exploitation" OR "explorative" OR "exploitative") AND TITLE-ABS-KEY("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network*" OR "generative AI" OR "natural language processing" OR "NLP" OR "large language model*" OR "LLM" OR "cognitive computing") AND TITLE-ABS-KEY("organi?ation*" OR "firm*" OR "business*")) AND PUBYEAR > 2014 AND PUBYEAR < 2027 AND (LIMIT-TO (SUBJAREA,"BUSI")) AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English"))

The full Boolean search string used in the Web of Science database is the following: ((TS=("organi?ational ambidexterity" OR ambidextro*) OR TI=("exploration" OR "exploitation" OR "explorative" OR "exploitative")) AND TS=("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network*" OR "generative AI" OR "natural language processing" OR "NLP" OR "large language model*" OR "LLM" OR "cognitive computing") AND TS=("organi?ation*" OR "firm*" OR "business*"))

3.2.2 Inclusion and Exclusion of Literature

Screening and exclusion criteria need to be disclosed and justified, as these decisions significantly impact results (Fisch & Joern 2018, 104; Tranfield et al. 2003, 216). Figure 6 illustrates the process of refining the search results in Scopus database.

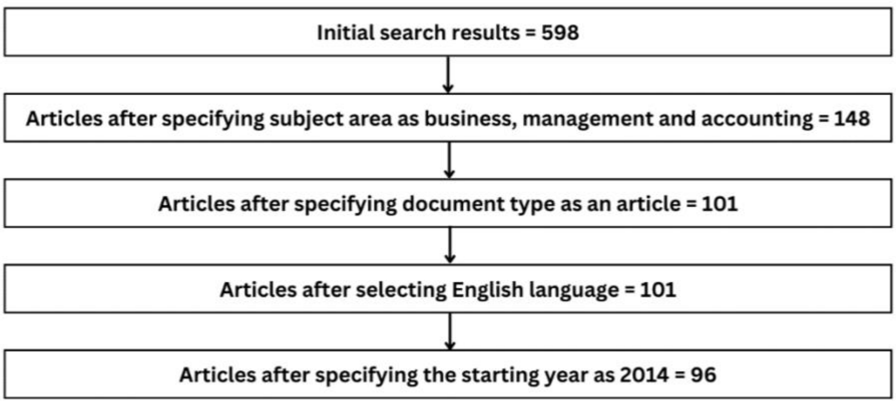

Figure 6. Inclusion and exclusion criteria for literature - Scopus

The initial search query in Scopus resulted in 598 articles. Since this research is being conducted on the organisational implications of AI technology advancements, the results were reduced to include only business, management and accounting domains. The second exclusion criterion aimed to refine results to articles, as these are usually published in journals, increasing the quality and trustworthiness of the results. Another screening criterion included selecting articles written in English due to the author's language limitations. In addition, only the articles published after 2014 were included because around this time the AI technology experienced significant progress, which expanded its practical relevance for businesses (LeCun et al. 2015, 436; Makridakis 2017, 47; Dwivedi et al. 2021, 2). Studies published before 2014 mainly address earlier generations of AI technology that no longer reflect the capabilities of the current technology and thus the findings of such studies may be deemed to be irrelevant (LeCun et al. 2015, 436; Makridakis 2017, 47; Dwivedi et al. 2021, 2). As a result, 96 articles passed this initial screening.

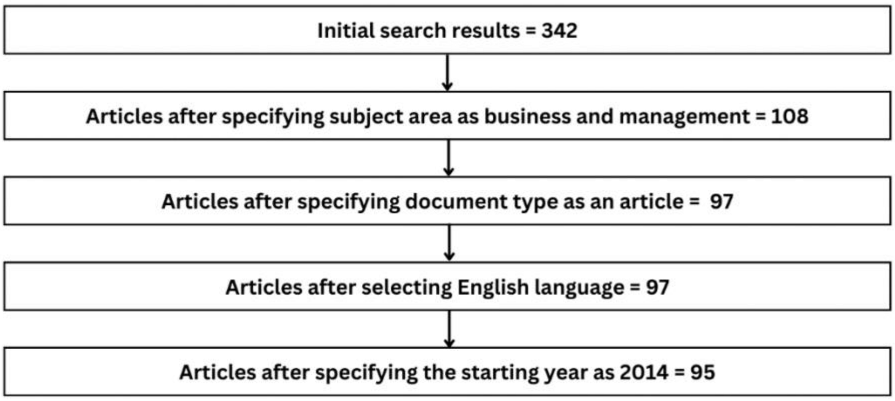

Figure 7. Inclusion and exclusion criteria for literature - Web of Science

The similar process was performed for the articles found on the Web of Science database. As seen on Figure 7, the initial search results delivered 342 articles. 95 articles remained after the subject area, document type, language and publishing year screening. The final refinement of the articles from both databases is illustrated in Figure 8.

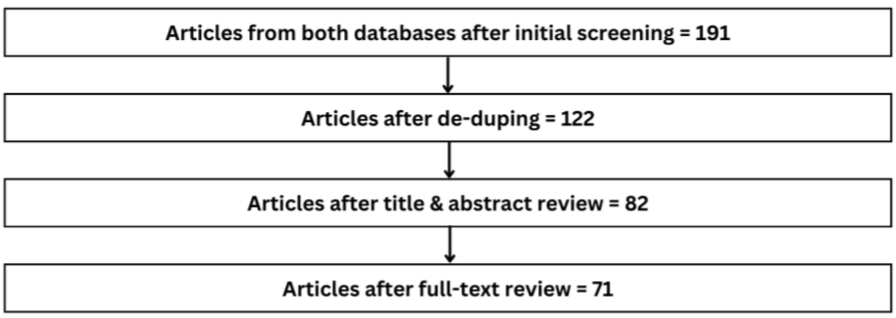

Figure 8. Final refinement of literature review results from both databases

After this initial screening, a total of 191 articles remained, as highlighted in Figure 8. Next, the results were further refined based on research aims. The goal was to include only the studies that contribute to this thesis's aims. Articles outside the scope of this research were not included. Furthermore, literature review articles were not selected to ensure that the analysis was grounded in original empirical research and to minimise the risk of double-counting previously synthesised insights. The articles were first screened based on their title and abstract, and then on the full text. As a result, 71 articles were selected for the literature review. The full list of articles and their authors, titles, journals and publication years are outlined in Appendix 1.

Another important aspect of systematic literature review research is the balance between breadth and depth. The maturity of the given research field has an impact on the selected breadth and depth approach. Generally, researchers need to analyse a large volume of literature if a subject is mature. On the contrary, when a topic is new, only a few studies have been published. (Fisch & Joern 2018, 104-105) In the case of this thesis, ambidexterity is an established concept. However, the field that explores the links between organisational ambidexterity and artificial intelligence is only emerging. This conclusion is supported by a relatively modest number of relevant articles identified for the literature review. Table 3 presents the operationalisation table.

Table 3. Operationalisation table

Research Aim	Sub-objectives	Themes	Chapter numbers
To synthesise a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation	To synthesise insights on how artificial intelligence impacts exploration	AI enabling exploratory innovation	2.1, 2.2, 4.2.1
		AI enabling sensing & seizing of new business opportunities	2.1, 2.2, 4.2.2
		AI fostering creativity	2.1, 2.2, 4.2.3
	To synthesise insights on how artificial intelligence impacts exploitation	AI enabling efficiency gains	2.1, 2.2, 4.3.1
		AI improving efficiency of business functions	2.1, 2.2, 4.3.2
		AI enabling exploitative innovation	2.1, 2.2, 4.3.3
		Ai improving decision-making	2.1, 2.2, 4.3.4
		AI as a learning assistant	2.1, 2.2, 4.3.5

The operationalisation table above illustrates how the research aim is translated into specific sub-objectives and themes. It provides a structured overview of how this research is organised. After the data has been collected, the research process continues to data analysis (cf. Tranfield et al. 2003, 214-219).

3.3 Data Analysis

Systematic literature review research needs to contain all relevant papers and comprehensively describe a phenomenon. However, the findings section should not include infinite descriptions of all research papers. Instead, only the most significant and relevant studies should be presented in detail. Furthermore, a literature review must synthesise new knowledge that advances the given field further. (Fisch & Joern 2018, 104-105)

This thesis examined and synthesised data using descriptive and thematic analysis. First, a descriptive analysis was executed, summarising the key findings of the selected articles. The literature was read starting with the oldest articles, and an Excel sheet was used to organise the data, including the authors' names, publishing year, title of the article, research methods used, main findings, findings regarding this thesis's research aims, and the author's notes. Furthermore, NVivo was utilised to code the keywords, phrases and sentences of all articles. (cf. Tranfield et al. 2003, 218)

The second step of data analysis focused on the thematic analysis. Based on the summaries and codes developed in the previous stage, the aim was to identify recurring themes. To accomplish this, both the codes from NVivo and the findings sections from the Excel sheet were used. The process of establishing themes was iterative, ensuring rigour in justifying the conclusions. (cf. Tranfield et al. 2003, 218-219) The example of the coding process is presented in Table 4.

Table 4. Examples of coding

Article	Quote	Codes	Themes	Analytical lens
Al-Khatib 2023, 9	"GEN-AI will enhance the opportunity for new EXPLORI and access to new opportunities."	AI enhancing opportunities for exploration	AI enabling exploratory innovation	AI-enabled exploration
Rizomyliotis et al. 2025, 1551	"Some respondents noted the potential for increased efficiency and cost savings through the automation of routine tasks, while others highlighted the potential for improved decision- making through the analysis of large volumes of data"	AI increasing efficiency, AI increasing cost savings, automation of routine tasks, improved decision-making	AI enabling efficiency gains	AI-enabled exploitation

Daskalopoulos & Machek, 2025	"We find evidence of partial mediation, as AI adoption directly and indirectly fosters ambidexterity through DMC"	AI enabling ambidexterity, direct impact of AI, indirect impact of AI, AI improving decision-making, mediating effect of AI	AI enabling efficiency gains, AI improving decision-making	AI-enabled exploitation

As Table 4 demonstrates, relevant quotes were highlighted in each article. After that, codes were generated at a granular level, often multiple codes emerging from one sentence. Only the content directly related to answering the research aim was coded. Related codes were later clustered into themes.

The thematic analysis initially followed an inductive approach to identifying recurring themes. This approach was selected because research on AI and organisational ambidexterity is still fragmented. Imposing a predefined coding framework could risk overlooking novel patterns across studies. Generating themes from the data itself allowed unexpected relationships between AI, exploration and exploitation to surface. However, the broad analytical lens was informed by ambidexterity theory, particularly in relation to the distinction between exploration and exploitation. This reflects a hybrid approach, where data-driven insights are organised according to a relevant existing theoretical structure. (cf. Fereday & Muir-Cochrane 2006, 82-83)

After conducting the analysis, the identified themes were analytically allocated based on their primary focus into one of the three categories: AI-enabled exploration, AI-enabled exploitation and AI-enabled organisational ambidexterity. Themes associated with experimentation, innovation and pursuit of new opportunities were categorised as part of exploration. Themes focusing on efficiency and optimisation were allocated to exploitation. The third category is a collection of themes that focus on simultaneous pursuit of exploration and exploitation through AI. The allocation of themes across these three categories is illustrated in Figure 9.

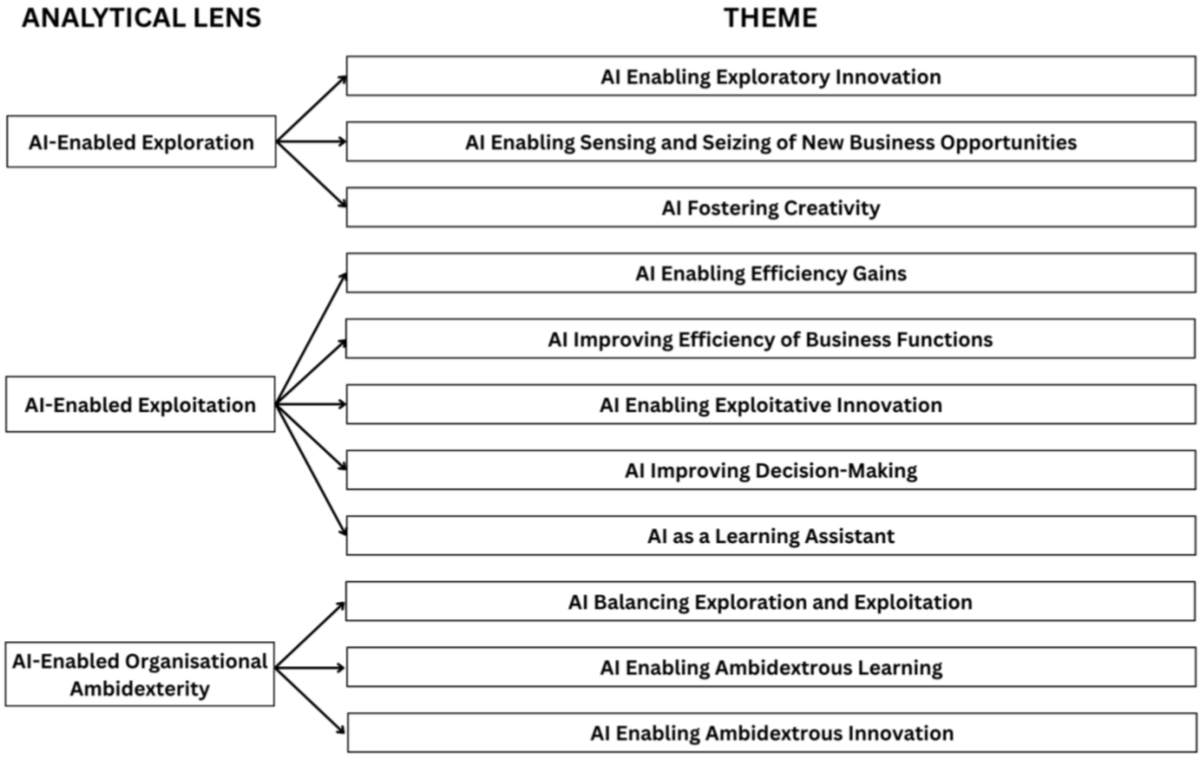

Figure 9. Identified themes

As can be observed in Figure 9, the thematic analysis of 71 articles resulted in identification of 11 themes. Under the AI-enabled exploration analytical lens, three themes are identified, such as AI enabling exploratory innovation, AI enabling sensing and seizing of new business opportunities, and AI fostering creativity. Under the AI-enabled exploitation, five themes are discovered, including AI enabling efficiency gains, AI improving efficiency of business functions, AI enabling exploitative innovation, AI improving decision-making, and finally AI as a learning assistant. Under the last lens – AI-enabled organisational ambidexterity – are three themes: AI balancing exploration and exploitation, AI enabling ambidextrous learning, and AI enabling ambidextrous innovation. The overview of the codebook from NVivo is presented in Appendix 2.

The themes outlined in Figure 9 form the basis for the synthesis presented in Chapter 4. The final stage of the systematic literature review is reporting the findings (Tranfield et al. 2003, 218). Fisch & Joern (2018, 105) suggest presenting the findings in a concept-centric way. Instead of writing about studies in chronological or alphabetical order, the studies can be grouped according to the concepts they represent that align with the study's aims (Fisch & Joern 2018, 105). Chapter 4 provides a thorough overview of the main findings in a structured, theme-based way. As the amount of data analysed is vast, tables and figures are used to capture the most essential information in a parsimonious way (cf. Fisch & Joern 2018, 105).

A literature review may result in the development of new conceptual frameworks (Fisch & Joern 2018, 105). Chapter 4 concludes with a framework of organisational ambidexterity in the context of artificial intelligence. The next subchapter discusses how this research was evaluated.

3.4 Evaluation of the Research

An important part of the research process is the quality evaluation. This thesis is evaluated based on the four trustworthiness criteria outlined by Lincoln and Guba (1985, 300). The first criterion is credibility, referring to the trustworthiness of the internal validity of the research (Lincoln & Guba 1985, 296; Schwandt et al. 2007, 12). To ensure the credibility of this study, a thorough engagement with the literature was undertaken. Each selected literature review article was studied in depth, increasing the accuracy of the interpretation and contributing to the recognition of the implicit findings. Additionally, several good quality databases were utilised, ensuring that only peer-reviewed articles are included. (cf. Schwandt et al. 2007, 18-19) This research includes a limitation in the form of inherently subjective interpretation of the literature – some nuances from original studies may have been overlooked despite careful analysis.

The second criterion to fulfil is transferability, which contributes to the applicability of the conducted research (Lincoln & Guba 1985, 297; Schwandt et al. 2007, 12). This study provided detailed descriptive data regarding the context and boundaries of the research. This supports transferability by allowing the readers to evaluate whether the findings apply to other fields. (cf. Schwandt et al. 2007, 19) However, the findings are based on English-language articles only, which may limit transferability to non-English or other less represented industries and geographies.

The third criterion is dependability, which contributes to the consistency and reliability of the research. An external examination of research by disinterested parties can enhance the dependability. (Lincoln & Guba 1985, 299; Schwandt et al. 2007, 12, 19) This thesis was audited by the supervisors, who checked the general validity of the findings. However, it is worth noting that this paper was written by only one author. The dependability of the findings could have been higher if more than one researcher had been involved in the cross-checking of data. (cf. Lincoln & Guba 1985, 297; Schwandt et al. 2007, 19) To mitigate this factor, the research process was documented and presented in detail. Another tactic contributing to the dependability of the research is the inclusion of Appendix 1, which outlines all articles that form the basis for the findings.

The fourth criterion is confirmability, referring to the objectivity of the study (Lincoln & Guba 1985, 300; Schwandt et al. 2007, 12). Conducting research with the help of thematic analysis presents a challenge to ensuring absolute objectivity. This thesis aimed to analyse the literature in as much of an objective manner as possible by following a systematic process of coding the keywords and constructing the themes based on data. In addition, the methodological steps of this research were disclosed. Considering ethical transparency, this study aimed to minimise selection bias by applying consistent inclusion and exclusion criteria when screening articles. Furthermore, the author sought to interpret and represent the selected research accurately, avoiding distortion of the original authors' findings. Yet it is important to mention that thematic analysis involves subjective interpretation, so the findings may still reflect the author's perspective, despite attempts to minimise bias. By conforming to these four criteria, research improves its trustworthiness and stability (Schwandt et al. 2007, 16).

4 Organisational Ambidexterity in the Context of Artificial Intelligence

The objective of this chapter is to fulfil the main research aim of this thesis by synthesising a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation. This chapter begins by presenting the descriptive results from the conducted research. Then, two sub-objectives are addressed by dedicating chapters to AI-enabled exploration and exploitation. After that, systematic literature review findings related to AI-enabled organisational ambidexterity are discussed. Finally, this section concludes with the synthesis of a conceptual framework.

4.1 Descriptive Findings on Artificial Intelligence and Organisational Ambidexterity

The 71 articles included in the systematic literature review were published in 58 different journals. These publications are presented in Table 5.

Table 5. Publications of the reviewed articles

Publication Title	Number of articles
Technology Analysis and Strategic Management	4
Technological Forecasting and Social Change	3
Journal of Manufacturing Technology Management	3
International Journal of Information Management	2
International Journal of Operations and Production Management	2
Journal of Family Business Management	2
Journal of Innovation and Knowledge	2
R and D Management	2
Technovation	2
Other journals with one article	49

As Table 5 shows, the most prevalent publications are Technology Analysis and Strategic Management, Technological Forecasting and Social Change, and Journal of Manufacturing Technology Management. All these journals concentrate on technological aspects, reflecting the artificial intelligence focus of this thesis. Additionally, the high diversity of the journals included indicates that the researched phenomenon is new, as it appears in multiple subfields of business studies.

As Chapter 3 specified, the articles were selected from 2014 onwards. Figure 10 illustrates the distribution of articles per year.

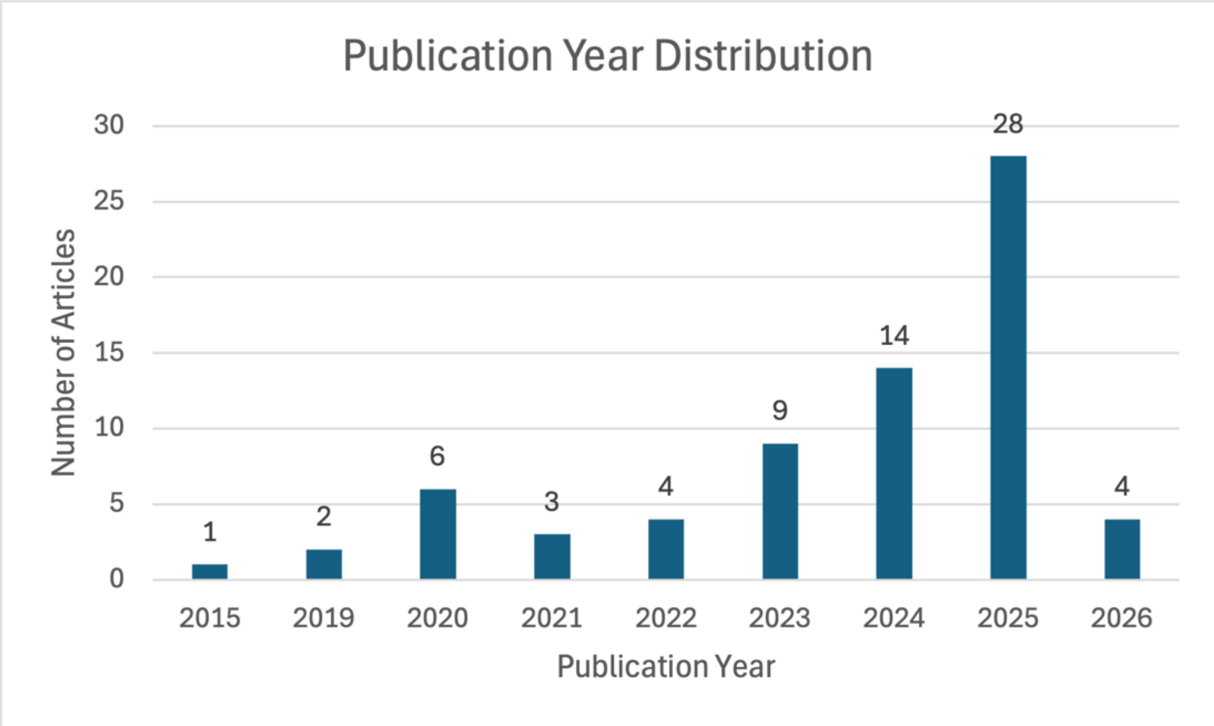

Figure 10. Distribution of articles per year

As is evident from Figure 10, most articles included are recent. Year 2023 experienced an uptick in the number of articles, with 2025 being the most common publication year. This trend can be explained by the rising interest in AI since the technology became widely available for the general public in 2022 (Triguero et al. 2024, 10). The observed trend reinforces the relevance of this thesis and highlights the need for a structured synthesis of emerging findings.

The selected articles apply various methodological approaches, including qualitative, quantitative and mixed methods. As mentioned in Chapter 3, studies utilising literature review as the methodology are not included in the analysis. The distribution of methodological approaches is shown in Figure 11.

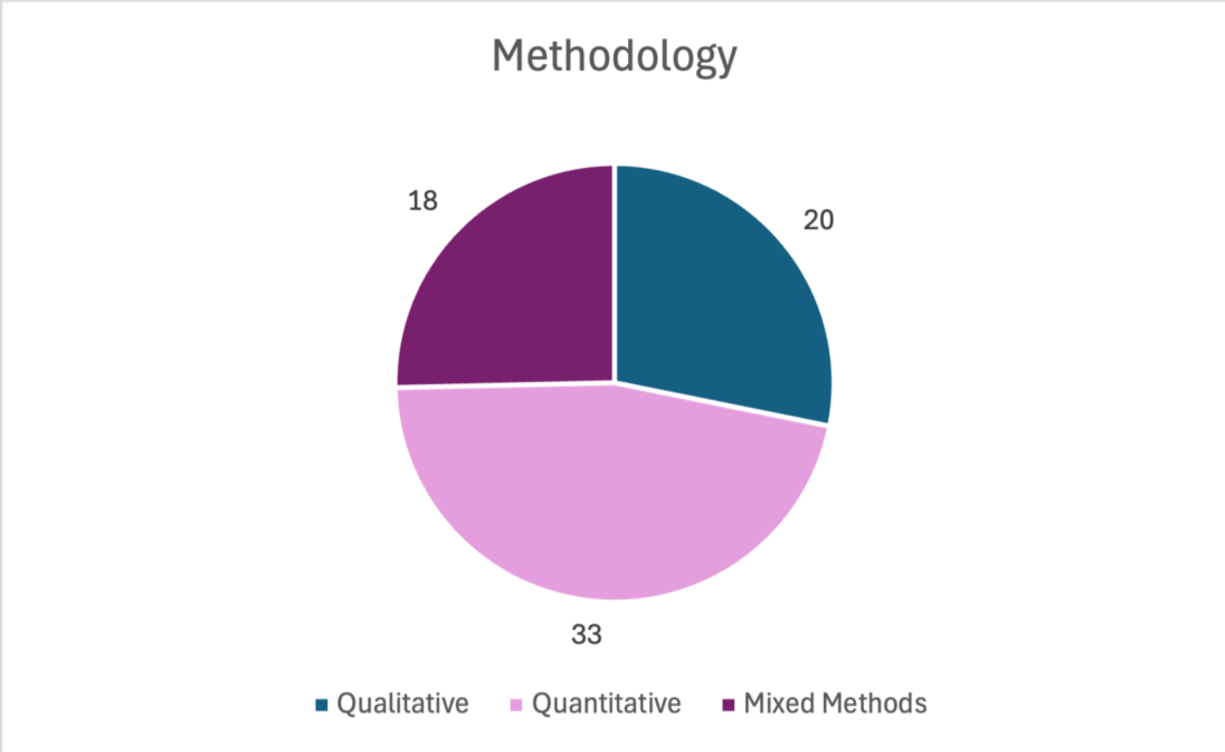

Figure 11. Methodological distribution

As Figure 11 highlights, the distribution of methodological approaches is almost equal between mixed methods and qualitative studies - 20 and 18 respectively. The quantitative approach proves to be the most common with 33 articles utilising this method. This could be explained by the fact that many articles aim to establish connections and relationships between variables, for instance, AI and exploration activities. This methodological diversity supports the robustness of this thesis by incorporating multiple perspectives on AI and organisational ambidexterity. Additionally, this diversity supports the need for synthesis, as it allows for findings derived from different methods to be integrated together.

Regarding the industry focus of the selected SLR articles, a wide variety can be observed. The most prominent industry is manufacturing, with 14 articles exploring this sector. Retail, healthcare, telecommunications, IT and entrepreneurship each have 2 articles. Other single articles include family business, agriculture, transportation, engineering, textile, hospitality, legal, automotive, finance and government. Some articles incorporate the findings from more than one industry. The full list of industries is showcased in Table 6. The inclusion of studies from a wide range of fields strengthens the review by reducing the risk of context-specific bias. As a result, patterns and themes can be observed beyond single-sector focus, offering broader conceptual insights.

Table 6. Distribution of industries

Industry	Count
Not specified	40
Manufacturing	14
Retail	2
Healthcare	2
Telecommunications	2
IT	2
Entrepreneurship	2
Family business, agriculture, transportation, engineering, textile, hospitality, legal, automotive, finance, government	1 each

As for the geographical distribution of the reviewed articles, the inclusion is also diverse. 13 articles focus on China, while 2 articles each explore Malaysia, Jordan, United Kingdom and United Arab Emirates. Other mentioned countries and regions include Indonesia, Europe, Greece, Morocco, Canada, Germany, Sweden, South Korea, Ghana, United States of America, Taiwan, Pakistan, Poland. The full geographical distribution is presented in Table 7.

Table 7. Distribution of geographies

Geography	Count
Not specified	38
China	13
Malaysia	2
Jordan	2
United Kingdom	2
United Arab Emirates	2
Indonesia, Europe, Greece, Morocco, Canada, Germany, Sweden, South Korea, Ghana, United States of America, Taiwan, Pakistan, Poland	1 each

Additionally, Figure 12 illustrates the spread of articles across world regions. More than half of the articles focus on the Asian region. Europe and the Middle East are also represented with sufficient numbers of articles – 7 and 4 respectively. The Americas and Africa regions each have 2 articles. This implies that almost all continents are included in this systematic literature review, ensuring representation of various cultures and organisational environments.

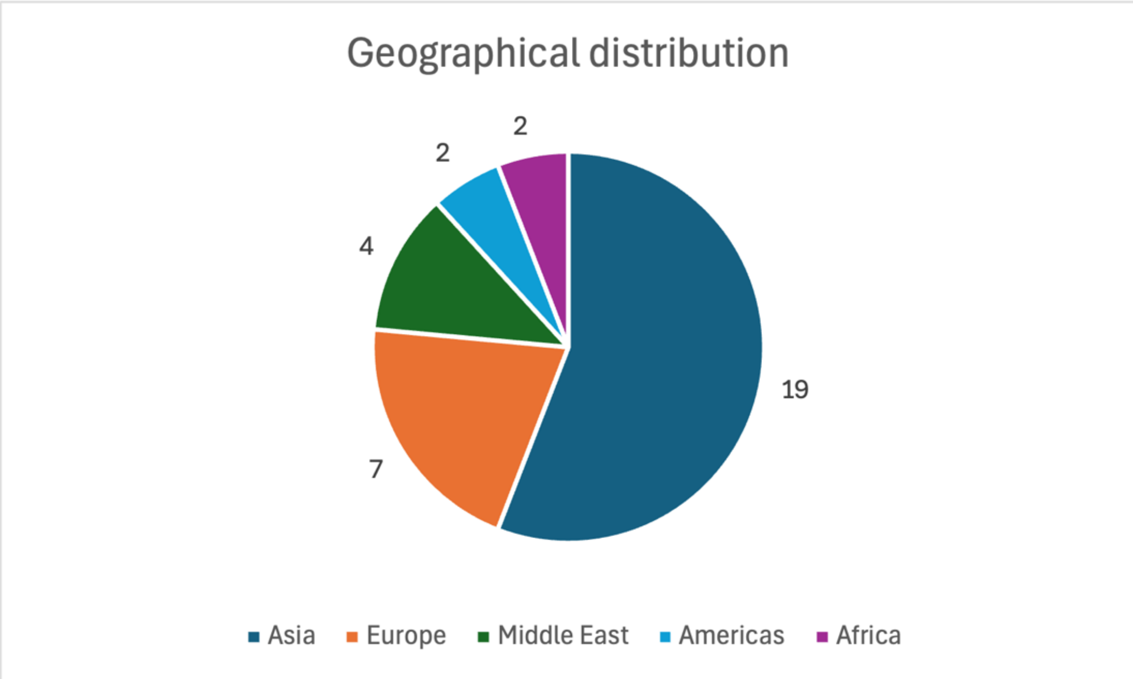

Figure 12. Geographical distribution

Overall, the descriptive results of the systematic literature review demonstrate a high level of diversity across journals, methodologies, industries and geographical contexts. This diversity reflects the emerging and interdisciplinary nature of the studied phenomenon. The predominance of recent publication years indicates that this is a novel and rapidly developing field, attracting research interest. The diversity of methodological approaches strengthens the comprehensiveness of this thesis by reducing context-specific bias and enabling identification of broader patterns. As a result, this diversity provides a solid empirical foundation for the development of the conceptual framework, ensuring that it captures patterns that extend across different contexts rather than reflecting isolated findings.

4.2 AI-Enabled Exploration

The findings in the exploration domain are further divided into three sub-chapters. These sub-chapters provide evidence on AI's impacts on exploratory innovation, sensing and seizing capabilities and creativity.

4.2.1 AI Enabling Exploratory Innovation

Upon reviewing the articles, it was discovered that the most prominent theme in the exploration domain is exploratory innovation. Numerous articles demonstrate positive effects of AI on exploratory innovation (Yun et al. 2021, 12; Al-khatib 2023, 1; Li et al. 2024, 3479; Daskalopoulus & Machek 2025, 11; Lou et al. 2025, 16; Rizomyliotis et al. 2025, 1551), with some articles indicating that AI may enable more radical forms of innovation (Gebauer et al. 2020, 1; Li et al. 2025a, 20):

> *"… AI technologies could enable new opportunities for innovation and product development by uncovering previously unrecognized patterns or insights."* (Rizomyliotis et al. 2025, 1551)

Taken together, the reviewed studies suggest that AI enhances exploratory innovation through the expansion of organisations' capability to identify novel patterns and generate ideas in ways that are difficult to achieve through traditional analytical approaches. It is important to note that while numerous reviewed articles advocate for positive impacts of AI on exploratory innovation (Al-khatib 2023, 1; Li et al. 2024, 3479; Lou et al. 2025, 16), the return on these investments and profitability remain questionable. A study on equipment manufacturers that devote monetary resources towards AI innovation, concludes that these advancements do not result in the expected monetary gains (Gebauer et al. 2020, 29). Another critical perspective is related to the expected outcomes of AI:

> *"A high exploration tendency weakens the performance-enhancing effect of AI adoption due to implementation instability caused by excessive experimentation."* (Hong et al. 2025, 295)

The authors note that AI technologies, being so complex, cause strains on workers bandwidth. They recommend managers to ensure strategic clarity when managing such projects. (Hong et al. 2025, 295) This highlights a key tension within exploratory innovation – while AI expands the scope of experimentation, excessive exploration may reduce performance due to attention fragmentation. This case also highlights the key issue of ambidexterity – the need to balance exploration and exploitation.

In terms of practical use of AI for exploratory innovation across various business functions, research shows a multitude of applications. AI-enabled exploratory innovation is linked to performance improvements in areas such as supply chains and customer service. One study on small and medium-sized enterprises discovers that AI-enabled exploratory innovation enhances supply chain financial performance (Lu et al. 2024, 424). Another study reveals that exploratory innovation positively mediates digital transformation and supply chain performance (Zhang et al. 2025, 1). Research also indicates that AI-driven customer service that incorporates data with AI supply chain planning, could facilitate innovation with the help of predictive logistics and inventory (Cao et al. 2025, 12).

Another practical application of AI innovation is in the research and development (R&D) field. Research shows that AI is often used in explorative R&D, not exploitative R&D (Johnson et al. 2022, 1). This suggests that AI is primarily utilised to alter and enhance human activities, instead of automating routine R&D tasks. AI can analyse a large number of data quickly and as a result, the costs of R&D are reduced, while the speed is increased (Johnson et al. 2022, 7; Lou et al. 2025, 16).

One curious application of AI-enabled innovation is for sustainability purposes. External forces, such as customers, investors and governments often urge businesses to innovate in a responsible and sustainable way (Hassani & Bougadir 2026, 1). Studies on manufacturing and retail firms suggest that innovation capabilities, including AI-supported "green" exploration activities, are important for achieving sustainable performance (Lee et al. 2024, 761; Wang & Zhang 2025, 1). In line with this, businesses could connect technology with ethics and environmental concerns when innovating (Hassani & Bougadir 2026, 12). Another study finds that generative AI could enhance exploratory innovation with the moderating effect of environmental dynamism and ethical dilemmas (Singh et al. 2024, 1).

However, existing studies indicate that the relationship between AI-driven exploration and sustainability is not uniformly positive. Research on environmental, social and governance ratings discovers that these ratings restrain exploratory innovation. Authors outline that the effect of environmental, social and governance ratings on exploratory innovation is weakened in situations of resource abundance, insignificant market competition and modest technology accumulation. (Liu et al. 2026, 1) This suggests that sustainability pressures may both enable and constrain AI-driven innovation, depending on organisational and environmental conditions. While AI can support green innovation and responsible business practices, external sustainability pressures, such as environmental, social and governance ratings, may constrain exploratory activities. Overall, the relationship between AI-enabled exploratory innovation and broader sustainability subject appears to be context-dependent.

Regarding the factors that affect AI-enabled innovative capabilities of the companies, several studies find that businesses need IT capabilities to create an ability to innovative with AI and gain competitive advantages (Alfarizi et al. 2023, 65; Lee et al. 2024, 750; Zhang et al. 2025, 1; Wang & Zhang 2025, 18). One study on manufacturing industry in China concludes that:

> *"Machine learning, natural language processing, and computer vision each demonstrate significant positive effects on exploratory innovation..."* (Li et al. 2025a, 20)

The authors note that it could be explained by the fact that AI tools can assist with radical innovation. More specifically, machine learning technology is capable of detecting patterns in complicated and large datasets, which could facilitate the discovery of new innovations. Natural language processing excels at incorporating text-based insights across multiple sources, promoting the creation of innovative concepts. Computer vision sometimes surpasses human capability of analysing visual information, introducing novel ideas for product design. (Li et al. 2025a, 20)

One study on AI and technology patents proposes a conceptual framework for managing AI innovations. The authors indicate that the success of AI innovations could be enhanced by aligning process management, structural arrangements and knowledge search. Process management refers to monitoring and improving organisational processes to ensure adherence to established workflows and facilitating innovative activities. Structural arrangements are formal organisational structures that affect how effectively firms can organise activities to support innovation. Finally, knowledge search refers to the process of identifying and integrating relevant knowledge for problem solving during innovation activities. (Lin & Maruping 2025, 1112-1114) This highlights that AI-enabled exploratory innovation is not only technology-driven but also depends on organisational capabilities.

Devoting enough investment into AI developments is another factor influencing the success of AI-enabled innovation. AI tools require significant resources to deliver valuable outputs, so CEOs could enable innovation by allocating enough monetary resources to the initiative (Lou et al. 2025, 17). On the opposite end of the investment spectrum, a few studies explore the interplay between AI and frugal innovation, which refers to a capability of a firm to develop high-quality inventions with limited resources (Al-kahtib et al. 2025, 8; Czyzewska-Misztal et al. 2025, 859). Research presents AI as an enabler of frugal innovation. By engaging in exploratory activities, such as collaborating with partners and gaining new insights, companies generate novel ideas for optimising resource allocation, enabling frugal innovation (Al-kahtib et al. 2025, 8). One study highlights that this new reality, where businesses use complex high-priced AI technology in an environment with scarce resources, is full of tensions. The tensions include cost versus quality, autonomous way of working versus collaborative, and consolidating learning for local needs versus global expertise. The authors recommend managers to navigate these tensions according to current needs, instead of pursuing a full resolution of the challenges. (Czyzewska-Misztal et al. 2025, 859) This further reinforces the idea that AI-enabled innovation introduces constraints that need to be actively managed.

Furthermore, the reviewed articles explore how learning and knowledge management influences AI-enabled exploratory innovation. Several reviewed studies indicate that AI expands the scope and speed of exploratory learning and innovation (Chin et al. 2025, 1169; Dai et al. 2025, 1; Yan et al. 2026, 12). AI allows employees to acquire external knowledge that used to be beyond their reach (Yan et al. 2026, 12). A study on 20,863 AI patents demonstrates that when organisations possess diverse knowledge, it positively influences exploratory innovation (Zhang & Luo 2020, 666). One study on manufacturing industry in Pakistan concludes that:

> *"… a higher level of knowledge management capability demonstrates a more pronounced positive correlation between knowledge sources and exploratory innovation."* (Waseel et al. 2024, 2116)

Collectively, these findings indicate that knowledge diversity and integration play an important role in translating AI technology into exploratory innovation outcomes. An additional factor impacting AI innovation is the presence of appropriate organisational support. Exploratory innovation requires organisational tolerance for uncertainty, ambiguity and risks. (Li et al. 2025a, 1) Additionally, one study outlines critical success factors (CSFs) to AI adoption:

> *"… in the exploration phase, the organisational factors, such as 'business case orientation', 'executive management support', and 'promotion of entrepreneurial culture and experimentation', are the most relevant CSFs."* (Solaimani et al. 2024, 445)

Another determinant influencing AI innovation is leadership support. The research shows that leadership and management support play a critical role in enabling exploratory innovation (Waseel et al. 2024, 2104; Solaimani et al. 2024, 445). Effective leaders foster an environment and mindset of creativity and exploration, where novel ideas are welcome, thereby enabling businesses to innovate. Furthermore, good leaders create collaborative environments where employees learn and create together. One study adds to this argument by demonstrating that knowledge sources mediate the relationship between leadership support and exploratory innovation. (Waseel et al. 2024, 2116) Another study on 20,863 patents in the AI domain showcases that a firm's knowledge potential and knowledge diversity positively affect exploratory innovation (Zhang & Luo 2020, 666). Additionally, research reveals that HR practices that enhance intellectual capital are important for enabling AI-driven innovation (Chin et al. 2025, 1181). Taken together, these findings reinforce the notion that

AI-enabled innovation is not driven by the technology alone but is also shaped by organisational and leadership factors that determine how knowledge is created and utilised. This suggests that effective leadership could act as an enabler of AI-enabled exploratory innovation.

Human and personality factors also influence how AI is used for innovation. Research shows that employees utilise AI in different ways. Some people use it strictly for efficiency purposes, not engaging in exploratory activities, while others view AI as a tool for sparking creativity and aiding in brainstorming (Callari & Puppione 2025, 5011). One study concludes that workers who view AI as a trustworthy tool and possess a proactive personality, are more active in using AI for exploratory activities (Kong et al. 2024, 278). Research also suggests hiring some employees that already possess required AI skills, who will drive strategic AI initiatives (Lou et al. 2025, 17). These findings indicate that the exploratory use of AI is not only dependent on organisational conditions, but also on individual behavioural traits.

Altogether, the findings indicate that AI plays a significant role in enabling exploratory innovation by supporting idea generation, R&D processes and exploratory learning. However, the impact of AI on innovation is influenced by organisational structure, leadership support, personality factors, industry context, technological configurations and company maturity. Importantly, the reviewed studies suggest that AI does not guarantee improved innovation outcomes on its own, but rather it amplifies existing organisational capabilities, as well as constraints. The evidence also highlights key tensions, including uncertain financial returns, sustainability trade-offs and balancing of exploration and exploitation.

4.2.2 AI Enabling Sensing and Seizing of New Business Opportunities

Another way in which AI influences exploratory activities is showcased in the form of sensing and seizing new business opportunities. Detecting market changes and responding to them in time is often essential for the survival of the business. Several articles conclude that AI enhances this activity. (van Rijmenam et al. 2019, 2; Al-khatib 2023, 9; Daskalopoulus & Machek 2025, 12; Hong et al. 2025, 310) Hong et al. (2025, 310) emphasises that:

> *"… AI not just as a tool, but as a capability that orchestrates resources to meet market demands."* (Hong et al. 2025, 310)

Several studies mention that AI and its related technologies could be used for sensing new business opportunities (van Rijmenam et al. 2019, 2; Kaur et al. 2019, 48; Al-khatib 2023, 9). Cognitive computing technologies, which are part of the AI system, are useful for discovering novel business opportunities. Traditional systems supporting decision making often use predefined logic, which often leads to missing some factors. Cognitive computing technologies, on the other hand, have more progressive analytical and learning capabilities and are able to generate insights based on both unstructured and structured data. These insights enable companies to make strategic decisions. (Kaur et al. 2019, 48) Similarly, big data analytics is described as:

> *"… a dynamic organisation capability that supports strategic decision-making in times of ambiguity and uncertainty."* (van Rijmenam et al. 2019, 2)

Taken together, the reviewed studies suggest that AI enhances sensing capabilities primarily by expanding the speed and depth of data analysis. More importantly, AI appears to shift opportunity recognition from rule-based evaluation towards data-driven discovery. This could enable organisations to identify emerging patterns and opportunities that would be difficult to detect through traditional analytical approaches.

Once new opportunities are discovered, they need to be materialised, or in other words, seized. AI technologies support businesses in transforming data into useful information, enabling the realisation of business opportunities (van Rijmenam et al. 2019, 2; Rehman 2025, 24). This process could be further transformed intro strategic actions, for instance, by forming strategic alliances or global strategic partnerships (Kaur et al. 2019, 49). One study, focusing on broader subject of ambidextrous dynamic capabilities, notes that Industry 4.0 technology, which include AI, is:

> *"… positively related to ambidextrous dynamic capabilities. Ambidextrous dynamic capabilities significantly mediate between industry 4.0 technologies and SMEs international performance."* (Rehman et al. 2025, 24)

This shows that AI does not only contribute to opportunity identification but also facilitates the transition from insights into concrete strategic initiatives. In its essence, AI could connect sensing and seizing activities of organisations. In addition, AI and related technologies could contribute to international activities and growth of the companies.

Across the reviewed studies, AI is portrayed as a powerful organisational capability, enhancing firms' ability to explore and exploit new business opportunities. AI technologies, such as cognitive computing and big data analytics assist companies in sensing new opportunities by generating insights from diverse data. These AI-enabled sensing capabilities translate into seizing activities, where firms act upon AI-driven insights. Several analysed articles focused on seizing and sensing opportunities in uncertain environments (van Rijmenam et al. 2019, 2; Rehman et al. 2025, 24), which is particularly useful in the current era of continuous disruptive change. Overall, the analysed articles suggest that AI reinforces exploratory organisational capabilities by strengthening both opportunity recognition and pursuit, which could help businesses navigate complex environments better.

4.2.3 AI Fostering Creativity

AI technologies affect another important aspect of exploration – creativity. Several studies indicate that AI helps to boost creativity of employees (Kronblad et al. 2023, 227; Plantec et al. 2023, 1; Callari & Puppione 2025, 5013; Pepple & Muthuthantrige 2026, 9). For example, one study states:

> *"Several pointed out that technology had allowed them to focus on and enhance the creative aspect of their profession."* (Kronblad et al. 2023, 227)

AI tools, such as M365 Copilot, could be used for brainstorming and idea exploration. The technology is particularly helpful during the beginning stage of the creative process. (Callari & Puppione 2025, 5013) Many people struggle with the "fear of the blank page" and the research suggests that AI could help overcome this issue. Across the reviewed studies, a common pattern can be observed – AI primarily supports creativity by facilitating initial idea generation. However, AI is not a tool that can fully replace humans in creative tasks:

> *"Exploratory innovation continues to require significant human confirmation of AI-created insights, which highlights the fact that AI supplements and does not eliminate human creativity."* (Khan et al. 2025, 16)

A number of studies link the previously discussed subject of explorative innovation with creativity (Plantec et al. 2023, 12; Waseel et al. 2024, 2115; Lou et al. 2025, 17; Khan et al. 2025, 16). One study on the corporate innovation in times of CEO turnover notes:

> *"Our findings highlight the importance of using AI to effectively shift corporate innovation and steer organizations towards uncharted frontiers of discovery and creativity."* (Lou et al. 2025, 17)

The same study emphasises that the technologies they use during the study only facilitate innovation and creativity and suggest exploring this connection again with the most recent changes in AI technology, such as large language models (Lou et al. 2025, 17). This suggests that AI-driven creativity could be closely related to the overall innovation process, where creative idea generation serves as an input for innovation activities. However, having access to AI technology is often not enough. Skilled team leaders could:

> *"... motivate employees towards both exploration and exploitation by nurturing creativity, empowerment and a shared vision, thereby fostering AI within organization."* (Waseel et al. 2024, 2115)

The study highlights that effective leadership is needed for realising the potential of AI and its effects on creativity. By exemplifying such leadership behaviours, firms can better ensure that AI tools are actually used to support exploratory and creative work rather than remaining underutilised. This indicates that managerial support could act as an important enabling condition for AI-supported creativity, which influences the realisation of AI potential in practice.

It is important to note that in the reviewed studies, AI is not portrayed as a tool fully substituting humans when it comes to creativity. Instead, it is represented as a tool for brainstorming and idea exploration. It is most useful during the beginning stage of the creative processes when it generates numerous ideas quickly, allowing for further refinement by an individual. By supporting the formation of creative ideas, AI significantly contributes to the exploratory side of innovation.

4.3 AI-Enabled Exploitation

The findings in the exploitation domain are further divided into five chapters. These chapters further elaborate on AI's impacts towards efficiency gains, efficiency of various business functions, exploitative innovation, decision-making and exploitative learning.

4.3.1 AI Enabling Efficiency Gains

The most predominant theme emerging from the analysed studies is the positive effect of artificial intelligence on efficiency achieved through exploitative activities. Numerous articles highlight that AI enhances internal processes and routines, resulting in increased efficiency. (Al-Khatib 2023, 9; Gizelis et al. 2023, 638; Wirtz et al. 2023, 1173; Khan et al., 2025; Rizomyliotis et al. 2025, 1551) This pattern suggests that AI is often used as a tool for refinement of existing organisational structures. In other words, AI-driven efficiency gains are primarily achieved through the optimisation of already established processes rather than the creation of entirely new ones.

Several studies highlight automation as one of the mechanisms through which AI enhances efficiency. By incorporating artificial intelligence into operations, certain tasks could be fully executed by AI instead of the employees, resulting in cost savings. (Gizelis et al. 2023, 638; Rizomyliotis et al. 2025, 1551; Daskalopoulos & Machek, 2025) For example, a study on the telecommunications industry, notes that AI adoption could optimise:

> *"…resource allocation by eliminating routine/manual tasks from the employees.*" (Gizelis et al. 2023, 638).

Taken together, these findings suggest that automation primarily contributes to efficiency by reducing manual and routine workload and allowing employees to focus on higher value tasks. Beyond automation, studies suggest that AI is found to improve existing business competencies and resources (Al-Khatib 2023, 9; Daskalopoulos & Machek 2025, 12). One study on family firms discovers that:

> *"AI advancements enable managers to optimise and expand resource availability through increased speed, agility, process automation, and improved knowledge management and diffusion. This resource expansion allows for more effective allocation toward building capabilities that support efficiency alignment and strategy adaptation."* (Daskalopoulos & Machek 2025, 12)

This indicates that AI enhances organisational resource allocation, which could strengthen exploitative capabilities over time. While efficiency gains are widely reported, it is important to note that several studies provide alternative viewpoints. Some research suggests that AI adoption may not directly translate into significant productivity gains, particularly in short-term scenarios or when a specific technology is used (Giudice et al. 2022, 1; Khan et al., 2025). For example, a study on AI humanoid robot reveals that the adoption of these robots does not directly increase labour productivity as could be expected. However, the same study shows that humanoid robots indirectly contribute to efficiency by creating new organisational routines. (Giudice et al. 2022, 1) This suggests that exploitative benefits may depend on how AI is embedded within existing workflows.

Another important factor affecting AI efficiency gains is personality and preferences of employees. A study on Microsoft 365 Copilot identifies several types of behaviours related to AI usage, including the 'efficiency-seeking type'. (Callari & Puppione 2025, 5001) People that belong to this group, typically use AI for increasing efficiency of administrative tasks, such as:

> *"… taking meeting minutes, summarising discussions, and proofreading emails. These features allow respondents to reduce the manual effort involved in repetitive tasks, enhancing the speed and accuracy of their workflows and creating a smoother operational process."* (Callari & Puppione 2025, 5010)

The tasks described above often require limited mental effort and oversight and are useful for incorporating into existing workflows. This reinforces the idea that AI is primarily adopted for efficiency gains in routine tasks. In comparison, other types of AI users utilise AI more often to improve productivity, creativity and ability to innovate (Callari & Puppione 2025, 5013), resembling more explorative patterns rather than exploitative. This means that the personality and preferences of employees affect how AI tools are used.

Overall, the findings indicate that artificial intelligence predominantly contributes to the increased exploitative efficiency gains. This is particularly evident in relation to process, competence and resource optimisation, and task automation. Across the analysed studies, AI is often portrayed as a tool for improving the existing processes of the businesses, rather than a force that creates new internal processes. However, these efficiency gains are not guaranteed and depend on organisational context.

4.3.2 AI Improving Efficiency of Business Functions

Expanding further on the subject of AI-enabled efficiency gains, several reviewed studies explore the influence of AI on exploitative activities of specific business functions (Gizelis et al. 2023, 642; Rashid & Rasheed 2025, 1; de Ruyter et al. 2020, 19). Starting with operations, studies show that AI tools enhance operational efficiency (Gizelis et al. 2023, 642; Cao et al. 2025, 8; Esposito et al. 2025, 3424). A study in the retail industry provides examples of AI being utilised for:

> *"AI-powered visual merchandising for store optimization; AI-powered category management for optimized product organization; AI-powered merchandising algorithms for localized product assortment; autonomous shelf-scanning robots for inventory tracking; AI-powered atmospheric control for in-store environment optimization."* (Cao et al. 2025, 8)

Furthermore, AI technology, in the form of wearables, aids in identifying urgent operating issues, thus streamlining the decision-making process (Esposito et al. 2025, 3408). Taken together, these studies suggest that AI primarily supports the operations function through monitoring and optimisation tasks, rather than by significantly altering the processes.

Furthermore, AI demonstrates improvements in efficiency of logistics and supply chain functions (Cao et al. 2025, 8; Rashid & Rasheed 2025, 1; Zhang et al. 2025, 1; Wang et al. 2024, 1). AI could be utilised for inventory forecasting, automated order placement and processing, efficient sorting systems to enhance logistics, and order execution with the help of robotics (Cao et al. 2025, 8). Additionally, AI could improve order demand forecasting, which enables:

> *"… management to plan scheduled maintenance shutdowns and most importantly to have adequate materials and labour on hand throughout the year. When you know about a coming*

> *spike in demand, you can contact your suppliers to make sure to keep your supply lines running efficiently."* (Gizelis et al. 2023, 640)

AI tools could enhance marketing activities by analysing vast amounts of data. For instance, marketing campaigns could improve efficiency and decrease cost of acquisition when algorithms interpret and incorporate data on transactions and interaction history. (de Ruyter et al. 2020, 19; Gizelis et al. 2023, 640; Cao et al. 2025, 11) Research also indicates that AI improves efficiency of the sales function by automating the process of monitoring and reporting sales KPIs and through chatbots (de Ruyter et al. 2020, 19; Fan et al. 2020, 967). A practical example of AI usage in sales function includes:

> *"AI can identify sales opportunities as service solutions based on conversational patterns and the general direction that an interaction is taking and can review contact history, incorporate customer profile information, suggest questions, the timing of providing certain information, and personalized costing and offerings."* (de Ruyter et al. 2020, 19)

A study on retail organisations expands on how AI could be deployed in customer service:

> *"AI customer service optimizes workforce allocation by automating inquiries and forecasting demand."* (Cao et al. 2025, 11)

Additionally, AI tools could be helpful during customer conversations, as they allow for information to be quickly visualised (Kronblad et al. 2023, 227). Overall, AI in marketing and sales appears to focus on leveraging data to target, personalise and automate interactions to make them more efficient, rather than discovering entirely new ways of executing marketing and sales tasks.

Finally, several reviewed articles also discuss how AI improves the efficiency of additional business functions, beyond core operations, supply chain, marketing and sales. For instance, one study states that cognitive computing technologies possess a capability to increase efficiency of project management by analysing real-time data and monitoring the progress of the projects (Kaur et al. 2019, 49). In the human resource management area, one study identifies the knowledge of AI technologies as a critical skill for job relevance, suggesting that companies could improve human resource efficiency by prioritising internal reskilling programs (Kar et al. 2021, 90). This suggests that in supporting functions, AI also contributes to efficiency by enhancing decision support and capability development.

Overall, across the reviewed articles, AI is consistently portrayed as a technology that enhances the efficiency of business functions, representing exploitative benefits. Rather than fundamentally altering organisational processes, AI is often deployed to automate monitoring activities, enhance forecasting accuracy and support routine activities.

4.3.3 AI Enabling Exploitative Innovation

Expanding the subject of innovation, studies show that AI enables not only exploratory, but also exploitative innovation (Lin & Chang 2015, 1195; Lu et al. 2024, 424; Lou et al. 2025, 16; Zhang et al. 2025, 1). Studies explain that AI affects exploitative innovation through enhanced efficiency (Li et al. 2025a, 1), for instance:

> *"… through reduced development times, improved solution quality, and enhanced capability transfer across related projects."* (Li et al. 2025a, 21)

Furthermore, digital knowledge management is shown to influence exploitative innovation (Zhang & Luo 2020, 666; Li et al. 2024, 3477; Li et al. 2025a, 21; Li et al. 2025b, 19). Cognitively challenging duties of employees are alleviated since AI can classify and group vast datasets (Li et al. 2025b, 19). In addition, knowledge management influences how AI operates:

> *"For exploitative innovation, new knowledge connections enable AI to apply proven optimization techniques across previously disconnected domains, creating unexpected efficiency gains through knowledge transfer and cross-pollination."* (Li et al. 2025a, 21)

Taken together, these findings suggest that exploitative innovation is not focused on the creation of new knowledge or routines, but rather optimisation of existing assets and processes. Additionally, AI-enabled exploitation activities are shown to facilitate frugal innovation. It could be explained by the fact that when businesses focus on existing resources and abilities, they discover ways to build similar quality products with fewer resources than initially utilised. (Al-kahtib et al. 2025, 9) Continuing the subject of frugal and sustainable innovations, a study on environmental, social and governance ratings among Chinese publicly listed companies concludes that these ratings facilitate exploitative innovation. The more public attention an organisation attracts, the stronger the impact of environmental, social and governance ratings on exploitative innovation. (Liu et al. 2026, 1) This pattern suggests that external environmental, social and governance scrutiny forces companies to refine existing products and processes to meet stakeholder expectations, which could foster incremental efficiency improvements.

The industry that a business operates in seems to have an impact on how it uses AI in relation to innovation. Empirical evidence indicates that government organisations employ AI for exploitative innovation by improving their current processes (Zhou et al. 2025, 20). Additionally, a study on automotive industry, which is represented as a traditional industry, highlights that such companies might experience difficulties integrating AI in innovation (Plantec et al. 2023, 1):

> *"... traditional industry incumbents may face challenges integrating such disruptive technology in their optimized new product development processes."* (Plantec et al. 2023, 1)

Authors conclude that traditional businesses utilise AI's ability to exploit data when creating AI systems, as a result enabling exploitative innovation (Plantec et al. 2023, 1). Taking these factors together, they indicate that the application of AI in exploitative innovation is context dependent, with more regulated environments favouring efficiency-oriented use of AI over exploratory innovation. Another factor influencing AI-enabled exploitative innovation is leadership and management support, which shows to enable innovation (Waseel et al. 2024, 2104).

As it was earlier indicated, AI could be used for both exploitative and exploratory innovation. It is important to highlight that some articles note that AI effects are more prominent in exploitative innovation, rather than exploratory (Plantec et al. 2023, 12; Cao et al. 2024, 1029; Li et al. 2025a, 19; Zhou et al. 2025, 20).). One study explains it by stating that:

> *"AI's stronger effect on exploitative innovation stems from its inherent pattern recognition capabilities that excel at optimizing existing processes, identifying inefficiencies in established workflows, and systematically improving current products and services. The algorithmic learning mechanisms enable firms to extract maximum value from existing knowledge bases by discovering previously unrecognized relationships within familiar technological domains."* (Li et al. 2025a, 19)

From the conducted review, it is noticeable that the academic community has not yet reached a consensus on whether AI impacts are more evident in exploratory or exploitative innovation. This lack of consensus suggests that the impact of AI on innovation could be dependent on organisational and contextual conditions, rather than being fully directed towards either exploration or exploitation. Empirical evidence supports this argument by showing that an organisational structure and industry impact its ability to innovate with AI (Zhou et al. 2025, 20). For instance, one study compares the impacts of generative AI on corporate and government organisations and reveals that corporate firms are more active in utilising AI technologies for exploratory innovation, since they need to continuously aspire for new advancements to remain competitive and drive profitability. Government organisations, on the other hand, exist primarily to serve the public instead of focusing all efforts on profit maximisation. Thus, government organisations engage more in exploitative innovation, concentrating on the refinement of existing processes. (Zhou et al. 2025, 20)

Another study reveals that individual AI technologies, such as machine learning, natural language processing and computer vision, indicate strong positive effect on exploratory innovation, however, not exploitative. The authors interpret these findings by stating that when the described technologies are combined in one system, the efficiency increases, which in turn, improves exploitative innovation. Yet, when applied to exploratory innovation, this method constrains it by connecting the systems and enabling path dependencies. (Li et al. 2025a, 20) This suggests that the configuration of AI tools plays a critical role in determining whether AI supports exploratory or exploitative innovation. One study on manufacturing businesses in China suggests that a company maturity level affects how it uses AI and its impacts:

> *"As firms progress through maturity stages, GenAI adoption becomes more strategic and is linked to greater innovation ambidexterity, balancing efficiency gains with radical AI-enabled breakthroughs."* (Khan et al. 2025, 1)

From an organisational ambidexterity perspective, this stronger effect on exploitation could be explained by firms possessing rich data and existing elaborate routines on the exploitative side, which makes these domains particularly susceptible to AI's strengths of pattern recognition and optimisation. In other words, AI currently amplifies the aspects of the business where processes are already structured, while more volatile exploratory activities seem to be more challenging to automate.

Overall, the reviewed articles indicate that AI primarily enables exploitative innovation by optimising existing processes, strengthening digital knowledge connections and facilitating incremental improvements. Industry examples from government and traditional automotive sectors suggest that organisations with strong regulatory constraints tend to use AI within established processes for efficiency enhancements of innovations, rather than for enabling radical change.

4.3.4 AI Improving Decision-Making

Another recurring theme of AI impacts on exploitation is related to decision-making. Several studies conclude that AI influences ambidexterity through improved decision-making processes (van Rijmenam et al. 2019, 36; Gizelis et al. 2023, 638; Alhaimer et al. 2025, 1; Daskalopoulos & Machek, 2025; Khan et al., 2025). A study on the role of AI in decision-making discovers the mediating factor of AI by directly and indirectly cultivating ambidexterity through decision-making comprehensiveness. Decision-making comprehensiveness refers to data-driven methodology of processing insights to reach conclusions. This AI approach to decision-making fosters ambidexterity. (Daskalopoulos & Machek, 2025) AI tools not only help make more informed decisions in complex situations, but additionally influence the initiating part of this process, making it more manageable when compared to starting from scratch without any AI help (Callari & Puppione 2025, 5013).

One study explores the mechanisms of AI in decision-making and compares it to traditional systems. The authors explain that in the traditional decision-making process that functions based on pre-defined rules, the required information often arrives with a delay, directly affecting the process (Kaur et al. 2019, 47):

> *"Traditional systems account for structured data that is highly organized and seamlessly accessible. However, our respondents noted that there are instances when they are faced with unanticipated circumstances that require access to information that is not part of available database. Such scenarios are not adequately considered in traditional decision support systems."* (Kaur et al. 2019, 47)

As a result, the lack of correct insights delivered on time negatively impacts the efficiency and effectiveness of decision-making. In contrast, cognitive AI systems are built with a comprehensive analytical and learning competence, aiding in the decision-making process, especially in complex and unorganised environments. (Kaur et al. 2019, 49) The authors conclude that:

> *"… inclusion of cognitive computing in place of traditional decision support systems can help deriving insights which can lead to formulation of more efficient and effective solutions to routine operational issues."* (Kaur et al. 2019, 49)

This comparison highlights that AI-enabled decision-making allows firms to respond more effectively to situations than traditional rule-based systems. Moreover, with the help of more precise forecasting due to AI, companies are able to make more informed decisions, which could help them improve sustainability (Al-kahtib et al. 2025, 9). This indicates that AI use for decision-making could introduce positive impacts beyond improvement of routine decisions, to broader strategic consequences.

However, it is important to highlight that the reviewed studies represent AI as a tool aiding the decision-making process but not fully replacing humans. As a study on Microsoft 365 Copilot underscores:

> *"M365 Copilot offers valuable guidance on complex or unfamiliar topics, which can boost their confidence in decision-making. By ensuring that important aspects are considered, M365 Copilot allows users to approach challenging tasks with a sense of assurance, similar to seeking a second opinion to gain a broader perspective on the matter at hand."* (Callari & Puppione 2025, 5014)

Yet, a study on R&D activities highlights that the current situation might change soon, as AI models improve with the help of more accurate algorithms and more data used in machine learning models (Johnson et al. 2022, 10). This raises a question about how organisations will preserve human oversight when AI's capabilities improve. In essence, it represents an emerging tension, reflecting a potential shift from AI as a decision-support tool towards a more autonomous role.

Overall, in the reviewed studies AI is portrayed as a useful tool for improving the decision-making ability of firms due to its power to process complex and dynamic information. AI reduces information bottlenecks and supports more comprehensive analysis of all available data. This reduces mental overload of employees, and could have positive influence on strategic initiatives, such as enabling sustainability. At the same time, current evidence suggests that AI mainly augments and complements, rather than replaces, humans in the decision-making process, although AI developments might gradually alter that.

4.3.5 AI as a Learning Assistant

The final pattern identified in the exploitation sub-domain is related to exploitative learning. Across the reviewed articles, AI is represented as a learning assistant that explains complex subjects, incorporates predictive analysis and empowers decision-making authority (Wu et al. 2021, 1389; Li & Yeo 2024, 367; Callari & Puppione 2025, 5014; Yan et al. 2026, 1). One study describes that the Microsoft365 Copilot tool is perceived as:

> *"… a learning platform – a supportive "assistant" – like a "second brain" – that suggests and provides diverse insights. This characterisation highlights the way M365 Copilot is considered as an auxiliary resource, extending users' capabilities without diminishing their role of agency."* (Callari & Puppione 2025, 5014)

This implies that AI could be used in cases where a second opinion is needed – a situation that used to require a colleague's opinion. Furthermore, AI provides an opportunity for employees to learn continuously and across disciplines (Li & Yeo 2024, 377). Interestingly, humans are able to not only learn from AI, but also teach AI (Li & Yeo 2024, 367; Yan et al. 2026, 1):

> *"AI's cognitive intelligence is capable of learning from each other through a process of deep learning. Humans, too, can learn from AI to modify their response towards working with AI-enabled applications."* (Li & Yeo 2024, 367)

One of the reasons for the effectiveness of AI in teaching humans could be the ease of access to the AI tools and the ability of these tools to explain information in simple terms. Another curious factor could be psychological safety. Since humans interact with a technological tool, instead of another human, they could experience more trust, openness and readiness to be vulnerable in asking questions, because the AI tool will not judge them (Li & Yeo 2024, 378). Collectively, these factors suggest that AI lowers both cognitive and social barriers to learning, making acquiring new knowledge more accessible within organisational settings.

Furthermore, AI supports processing of existing data, facilitating the repurpose and utilisation of existing insights. In other words, AI could be applied to internal learning. However, in such cases, employees might feel reluctant to use AI beyond these boundaries to uncover new knowledge. (Yan et al. 2026, 12) This indicates that while AI strengthens the efficiency of knowledge utilisation, it may simultaneously constrain the scope of learning by reinforcing existing routines.

Taken together, the reviewed articles showcase that AI could function as an exploitative learning partner, teaching humans in an accessible and psychologically safe way. Through this interaction, the reuse of existing knowledge is enabled and strengthened, while also enriching the knowledge of employees. Yet this internal focus risks creating overreliance on efficiency gains in processing existing data, discouraging employees to venture beyond these boundaries. In essence, this creates the classic exploration-exploitation tension, where focus on only one activity leads to negative consequences for the other. This suggests that organisations should actively manage these dynamics and utilise AI for both exploratory and exploitative learning to ensure long-term adaptability.

4.4 AI-Enabled Organisational Ambidexterity

The previous two chapters focused on the functional effects of AI on exploration or exploitation separately. Yet organisational ambidexterity emerges when these two activities are in balance. This chapter describes the ways through which AI enables organisational ambidexterity. Several articles highlight that AI not only affects exploration or exploitation activities of companies separately, but organisational ambidexterity as a whole (Kaur et al. 2019, 43; Lee et al. 2023, 19; Cao et al. 2025, 1; Daskalapoulus & Machek 2025, 12; Hassani & Bougadir 2026, 1). Some studies conclude that AI technology serves as the main precursor to organisations fostering ambidextrous capabilities (Daskalapoulus & Machek 2025, 12; Li et al. 2025b, 19). The main argument is that AI allows business leaders to create organisational environments that can balance stability and change (Daskalapoulus & Machek 2025, 12):

> *"Our results indicate that AI advancements enable managers to optimise and expand resource availability through increased speed, agility, process automation, and improved knowledge management and diffusion. This resource expansion allows for more effective allocation toward building capabilities that support efficiency alignment and strategy adaptation."* (Daskalapoulus & Machek 2025, 12)

This suggests that AI contributes to ambidexterity by expanding organisational capacity, which can be strategically allocated between exploratory and exploitative activities. Effectively balancing exploration and exploitation activities of businesses is the fundamental idea of organisational ambidexterity. Research demonstrates that AI adoption can help firms balance both of these activities (Wofford et al. 2020, 267; Wirtz 2020, 8; Khan et al. 2025, 2). This notion is further supported through research showing that AI influences ambidexterity when it is utilised not in isolation (Cao et al. 2025, 1):

> *"... the ability to reconcile efficiency and innovation does not stem from individual AI functions but from their coordinated deployment. ... It marks a shift from viewing AI as a set of siloed tools toward understanding it as a dynamic configuration that enables ambidextrous outcomes."* (Cao et al. 2025, 13)

A study on the telecommunications industry in South Korea sheds light on how ambidexterity could be implemented in practice. The authors share an insight that big traditional corporations, that are often too rigid and slow, could establish independent units within a company with a purpose of developing new businesses with the help of ambidexterity (Lee & Kim 2020, 10):

> *"... ambidextrous organization is an organization that explores new opportunities while exploiting the core legacy competence. Such a firm innovates legacy products to gain competitive advantage and, at the same time, acquires new knowledge/capability to develop new innovative products to enter into a new market."* (Lee & Kim 2020, 10)

One way that AI is enabling organisational ambidexterity is by connecting separate knowledge units together. Once the information gap is bridged, an opportunity for making more effective routine decisions arises, together with novel exploratory ideas (Kaur et al. 2019, 50; Krzywdzinski & Butollo 2022, 181). This principle also shows in connecting business units together:

> *"… AI-enabled business functions enhance firm performance not through isolated applications but through a strategic combination across business processes. The impact of AI varies depending on how firms configure these functions to optimize efficiency, foster innovation, or achieve both."* (Cao et al. 2025, 11)

This reinforces the idea that AI could act as an integrative mechanism, simultaneously supporting efficiency and innovation. Furthermore, AI is shown to promote ambidextrous learning (Wu et al. 2021, 1389; Yan et al. 2026, 1). This could be explained by AI's dual role in the learning process. On one hand, AI could be used for efficient processing of existing knowledge, thereby facilitating exploitative learning. On the other hand, AI could be utilised for exploratory learning through exposure to new information and patterns. This way, businesses could use AI tools to simultaneously deepen existing competencies while also creating new knowledge. Additionally, research indicates that AI may enable ambidextrous innovation by allowing firms to simultaneously refine existing products and develop new offerings (Yun et al. 2021, 12; Li et al. 2024, 3477; Li et al. 2025a, 1).

However, the reviewed studies also include alternative viewpoints on AI's impact and role in organisational ambidexterity. A study on the manufacturing industry in China suggests that ambidextrous strategy reduces the positive outcomes of AI adoption (Hong et al. 2025, 311):

> *"Our findings show that ambidextrous firms – those that simultaneously pursue high levels of exploration and exploitation – are particularly vulnerable to attention fragmentation. In such firms, managerial attention is divided between competing priorities: investing in AI infrastructure to enhance operational efficiency (exploitation) versus directing resources toward AI-driven innovation and experimentation (exploration). This tension dilutes the depth of attention allocated to either domain, thereby constraining the full realization of AI's potential."* (Hong et al. 2025, 311)

In other words, this study argues that the reality of limited attention evolves into a critical bottleneck, particularly given the intricacy of AI technologies (Hong et al. 2025, 311). A study on explorative and exploitative R&D activities expands this claim further. The authors state that when businesses focus on developing several AI components simultaneously, the likelihood of ambidexterity challenges increases, in particular, a firm's capability to explore and exploit the same technology in parallel (Johnson et al. 2022, 10). Taken together, these contrasting findings suggest that AI does not automatically enhance organisational ambidexterity, but possibly amplifies existing organisational constraints. AI seems to be capable of increasing the capacity of firms to pursue both exploration and exploitation, while also intensifying demands that are required to manage these activities. Thus, AI-enabled ambidexterity could be viewed not only as a technological challenge, but also a managerial one, where limited attention and resource allocation determine if AI's potential is realised or constrained.

Several reviewed articles support this conclusion by revealing that management approaches have an effect on AI-driven ambidexterity. The research shows that in order to foster ambidexterity, managers need to continuously balance organisational structures, priorities and resources between exploration and exploitation (Krzywdzinski & Butollo 2022, 179; Waseel et al. 2024, 2115). Furthermore, culture and organisational structure are shown to impact how AI tools could be applied to foster ambidexterity (Kronblad et al. 2023, 217; Solaimani et al. 2024, 445). One study compares law companies with architecture companies and finds that mature architecture ones are capable of balancing exploration and exploitation, while mature law organisations tend to prioritise exploitation. At the same time, new legal companies concentrate on exploration. (Kronblad et al. 2023, 217) This suggests that the focus could be dependent on the industry requirements, professional culture and maturity of the business. For instance, established firms could be more inclined to rely on exploitation because of the existing traditional organisational incentive schemes that could value exploitation more than exploration.

Overall, the reviewed articles imply that AI enables organisational ambidexterity not through a single function, but through a set of interconnected processes. These include knowledge integration, enhanced decision-making, and facilitation of ambidextrous learning and ambidextrous innovation. Importantly, the findings of this study indicate that the effectiveness of these mechanisms is dependent on organisational context, culture and managerial capabilities. AI appears to positively impact organisational ambidexterity when the tensions between exploration and exploitation are successfully managed. This suggests that achieving AI-driven ambidexterity requires appropriate organisational structure that allows businesses to continuously balance competing priorities.

4.5 Conceptual Framework of AI-Driven Organisational Ambidexterity

This chapter integrates the findings of the chapters 4.2, 4.3 and 4.4 and synthesises them into a conceptual framework. The main research aim of this thesis was to synthesise a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation. Since the existing literature provides a fragmented view on how AI affects ambidexterity (cf. Johnson et al. 2022; cf. Hong et al. 2025; cf. Wang & Zhang 2025), this framework illustrates how AI may enable organisational ambidexterity. The framework combines organisational and contextual conditions, AI capabilities, mechanisms, exploration and exploitation activities, ambidexterity and key tensions, and proposes a conceptual explanation of how these parts interact. In its essence, AI capabilities, together with organisational conditions, could activate a set of mechanisms that enable both exploratory and exploitative activities, ultimately shaping organisational ambidexterity. The full model is presented in Figure 13.

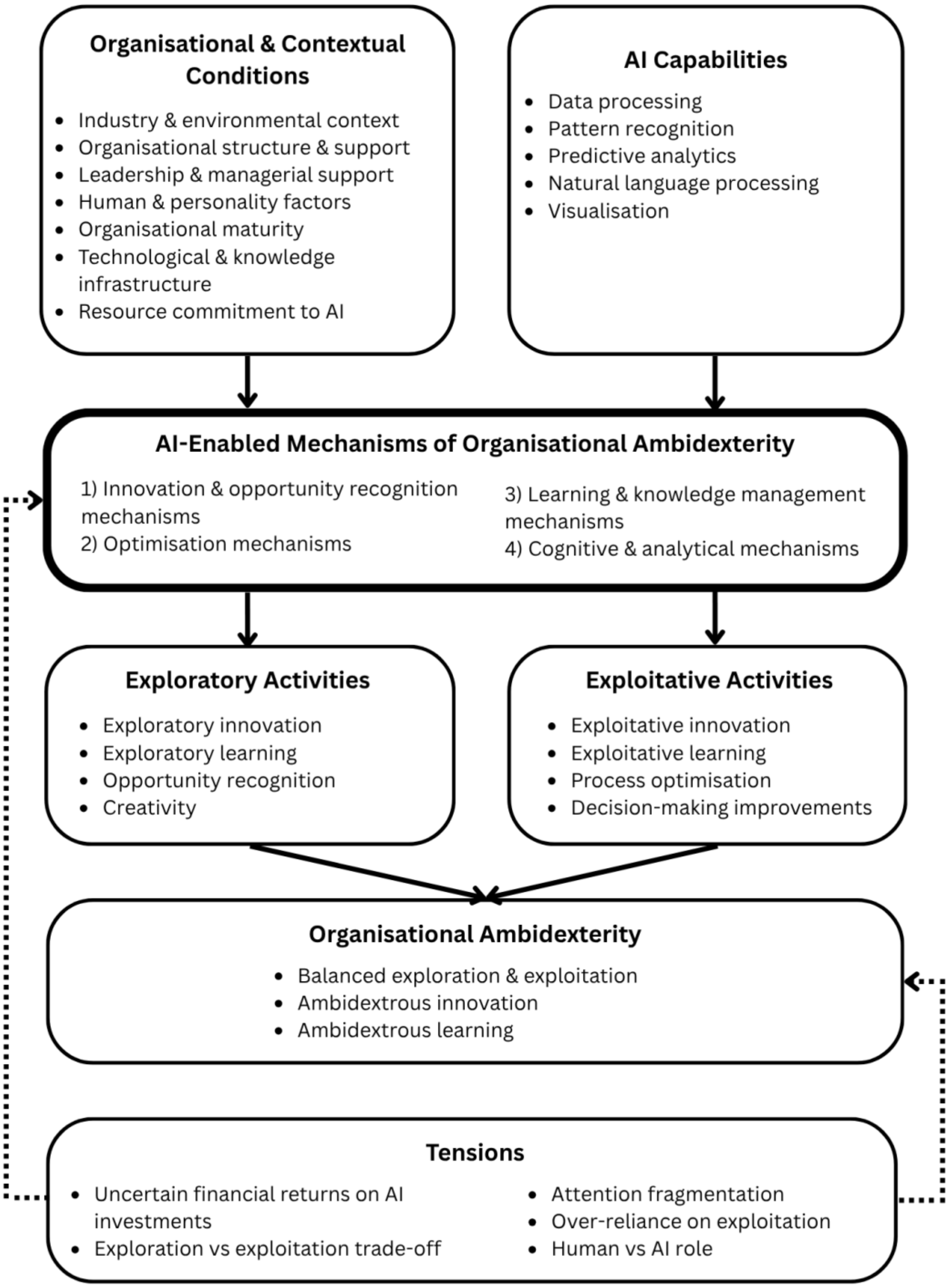

Figure 13. Conceptual framework of AI-driven organisational ambidexterity

Organisational and contextual conditions included in the framework highlight that the use and impact of AI are context dependent. Simply integrating AI into various business functions does not guarantee creation or enhancement of organisational ambidexterity. The effects of AI are dependent on several internal and external conditions. The first condition is industry and environmental context. This external context shapes how businesses prioritise exploration and exploitation activities, which influences how AI is deployed across different functions. For instance, firms operating in fast-paced, highly competitive environments may be more inclined to leverage AI for exploration, while firms in more stable and regulated environments may rely on AI for exploitative activities (Plantec et al. 2023, 1; Kronblad et al. 2023, 217; Zhou et al. 2025, 20).

The second condition is organisational structure and support (Solaimani et al. 2024, 445; Lin & Maruping 2025, 1112-1114; Li et al. 2025a, 1). Depending on how flexible or rigid an organisation is, it influences its ability to support both exploration and exploitation activities simultaneously. This condition could either enable cross-functional collaboration and experimentation, reinforce ambidexterity, or constrain it.

The third condition is leadership and managerial support, which is critical for setting strategic direction for AI use (Krzywdzinski & Butollo 2022, 179; Solaimani et al. 2024, 445; Waseel et al. 2024, 2115). Managers influence how employees use AI and whether they prioritise exploration, exploitation, or strive to achieve the balance of both.

The fourth condition is human and personality factors, demonstrating that employees' willingness to use AI and preferences impact outcomes (Kong et al. 2024, 278; Callari & Puppione 2025, 5011; Lou et al. 2025, 17). For instance, an employee's inclination to use AI primarily for exploitation may lead to over-reliance on this activity and lack of balance needed for ambidexterity.

Organisational maturity is the fifth condition, suggesting that mature firms tend to favour exploitation, while less mature ones could be more exploration-oriented (Kronblad et al. 2023, 217; Khan et al. 2025, 1). This implies that maturity affects how AI is utilised strategically and whether organisations rely primarily on one of the two activities.

Another factor is technological and knowledge infrastructure, which represents an internal foundation for the AI-enabled mechanisms to function. IT capabilities enable the implementation of AI tools within the organisation (Alfarizi et al. 2023, 65; Lee et al. 2024, 750; Wang & Zhang 2025, 18). Knowledge systems enable knowledge sharing and learning across business units (Zhang & Luo 2020, 666; Lin & Maruping 2025, 1112-1114). These two conditions could support both innovation and efficiency, fostering ambidexterity.

Lastly, resource commitment to AI represents the final condition (Zhang & Luo 2020, 666; Li et al. 2024, 3477; Li et al. 2025b, 19). Since AI implementation requires large financial investments, time and skilled workforce, the higher investment could affect the success and outcomes of AI's impacts on ambidexterity. These conditions collectively demonstrate that AI-driven organisational ambidexterity is dependent on several internal and external factors. The conditions may determine how AI is used and which mechanisms are activated.

The next construct in this conceptual framework is *artificial intelligence capabilities*. This construct outlines the key technical capabilities that AI technology possesses, which enable mechanisms of organisational ambidexterity. The first AI capability is data processing, which allows AI tools to process large volumes of structured and unstructured data (Kaur et al. 2019, 48; de Ruyter et al. 2020, 19; Gizelis et al. 2023, 640). With the help of data processing, the speed and depth of data analysis could be increased. This capability acts as a foundation for all other ones. The second capability is pattern recognition. It identifies relationships and trends in data, which is important for both innovation and efficiency enhancements (Kaur et al. 2019, 48; Rizomyliotis et al. 2025, 1551; Li et al. 2025b, 19). The third capability is predictive analytics, which utilises historical data to forecast future outcomes. This is particularly useful for strategic and operational tasks, such as trends prediction and complex decision-making (Wu et al. 2021, 1389; Li & Yeo 2024, 367; Callari & Puppione 2025, 5014; Yan et al. 2026, 1). The fourth capability is natural language processing, allowing generation of text (Li et al. 2025a, 20). This capability could be applied across various business and job functions, facilitating knowledge sharing and content creation. The final capability is visualisation, which enables analysis, interpretation and creation of visual data (Kronblad et al. 2023, 227; Li et al. 2025a, 20). Together and on their own, these capabilities could expand the cognitive and analytical ability of organisations, yet they may not directly translate into value on their own. In order to function for ambidexterity purposes, these capabilities may require mechanisms described in the following paragraph. In other words, AI capabilities represent the potential that AI has to offer, while mechanisms explain the realisation of that potential.

AI-enabled mechanisms of organisational ambidexterity are the core element of this conceptual framework. These mechanisms are based on the synthesis of the recurring themes observed across the reviewed articles. Individual studies tend to describe specific outcomes of AI adoption for ambidexterity purposes, such as improved efficiency, learning and innovation. However, these effects are often presented in isolation. By grouping these fragmented findings into higher-level categories, this thesis aims to provide a conceptual explanation of how AI creates ambidextrous value. As a result of the synthesis, four core mechanisms are identified, representing distinct yet interconnected pathways through which AI may influence exploratory and exploitative activities. The first mechanism is related to innovation and opportunity recognition. It enables idea generation and creativity (Johnson et al. 2022, 7; Callari & Puppione 2025, 5013; Lou et al. 2025, 16), as well as sensing and seizing of business opportunities (Kaur et al. 2019, 48). Hence, this mechanism is more exploration focused, as it acts as a catalyst for explorative innovation. The second mechanism is focused on optimisation and improving efficiency of operations. It acts primarily through resource optimisation (Al-Khatib 2023, 9; Daskalopoulos & Machek 2025, 12; Hong et al. 2025, 310) and process automation and optimisation (Gizelis et al. 2023, 638; Callari & Puppione 2025, 5010; Daskalopoulos & Machek 2025, 12; Rizomyliotis et al. 2025, 1551). This implies that this mechanism is primarily associated with exploitative value creation. The third mechanism is learning and knowledge management mechanism, which enables integration of diverse knowledge sources (Waseel et al. 2024, 2116; Chin et al. 2025, 1169; Dai et al. 2025, 1; Daskalopoulos & Machek 2025, 12). Additionally, it allows continuous exploratory and exploitative learning, as this mechanism supports creation of new knowledge and reuse of existing knowledge. In its essence, this mechanism could act as a bridge between exploration and exploitation. The fourth and final mechanism is cognitive and analytical mechanism, which enhances decision-making processes (van Rijmenam et al. 2019, 2; Kaur et al. 2019, 49; Gizelis et al. 2023, 638; Esposito et al. 2025, 3408). Through this mechanism, both strategic and operational decisions are supported. At the core, this mechanism appears to function as a central integrative element, connecting all other parts together. While each mechanism is associated with specific outcomes, this framework suggests that the mechanisms are not mutually exclusive. In practice, multiple mechanisms may be deployed simultaneously. Overall, whether AI is used to support exploration, exploitation or both activities, it seems to be influenced by which mechanism is activated. These mechanisms could explain why using similar AI technologies may lead to different organisational outcomes.

If the mechanisms influence exploration, *exploratory activities* may be enabled. These activities were described in detail in chapter 4.2 and include exploratory innovation (Al-khatib 2023, 1; Li et al. 2024, 3479), exploratory learning (Zhang & Luo 2020, 666; Waseel et al. 2024, 2116; Yan et al. 2026, 12), opportunity recognition (van Rijmenam et al. 2019, 2; Al-khatib 2023, 9; Daskalopoulus & Machek 2025, 12) and creativity (Kronblad et al. 2023, 227; Callari & Puppione 2025, 5013; Pepple & Muthuthantrige 2026, 9). AI, through the mechanisms, could enhance the speed and scale of exploration.

When the mechanisms activate exploitation, *exploitative activities* could be enabled. Described in more detail in chapter 4.3, these activities comprise of process optimisation (Al-Khatib 2023, 9; Gizelis et al. 2023, 638; Rizomyliotis et al. 2025, 1551), decision-making improvements (van Rijmenam et al. 2019, 36; Daskalopoulos & Machek, 2025; Khan et al., 2025), exploitative innovation (Lin & Chang 2015, 1195; Lou et al. 2025, 16; Zhang et al. 2025, 1) and exploitative learning (Li & Yeo 2024, 367; Callari & Puppione 2025, 5014; Yan et al. 2026, 1). Thus, AI could strengthen the efficiency of organisations.

Once businesses participate in both AI-enabled exploration and exploitation activities, *organisational ambidexterity* may be enabled. AI could enable a balanced pursuit of both exploration and exploitation (Wofford et al. 2020, 267; Wirtz 2020, 8; Daskalapoulus & Machek 2025, 12; Khan et al. 2025, 2). Achieving this balance is essential for the long-term performance of businesses. Furthermore, ambidextrous innovation could be achieved, providing the ability for firms to both generate radical innovations and improve existing offerings (Al-khatib 2023, 1; Lou et al. 2025, 16; Lin & Chang 2015, 1195). In addition, ambidextrous learning could be enabled, allowing businesses to acquire new knowledge and reuse existing knowledge (Wu et al. 2021, 1389; Yan et al. 2026, 1). Collectively, AI enables ambidexterity by connecting knowledge and supporting parallel activities. However, it is important to note that AI does not automatically ensure the balance of exploration and exploitation.

In fact, the reality of the world is full of complexities, which lead to several *tensions*. Starting with uncertain financial returns (Gebauer et al. 2020, 29; Giudice et al. 2022, 1), AI implementation often requires high investment. However, it is not guaranteed that the investment will result in an immediate return in terms on financial or productivity gains. Another tension is related to the core issue of ambidexterity – exploration and exploitation trade-offs (Hong et al. 2025, 295). Achieving the correct balance of these two activities is a challenging task. When resources are limited, investment could be directed primarily into one activity. AI, being a demanding investment, could intensify the competition between the priorities. Related to this issue, attention fragmentation presents another tension (Johnson et al. 2022, 10; Hong et al. 2025, 311). Managers must divide their attention between innovation and efficiency enhancement activities (Yan et al. 2026, 12). AI increases the complexity of decisions, which could reduce the depth of focus. Furthermore, AI is often used for efficiency gains, creating over-reliance on exploitation (Yan et al. 2026, 12). This could lead to underinvestment in exploration activities, risking business stagnation. Finally, the last tension is the human versus AI roles (Callari & Puppione 2025, 5014; Daskalopoulos & Machek 2025, 12; Khan et al. 2025, 16; Rizomyliotis et al. 2025, 1551). Since the technology is evolving rapidly, it creates questions about which tasks could be fully automated, and which still require human oversight and judgement. All in all, these tensions could constrain or moderate the outcomes of using AI for ambidexterity purposes, as they may impact the mechanisms. AI does not eliminate organisational tensions. In fact, it introduces or amplifies some of them. Managing these tensions effectively is essential for achieving and sustaining ambidexterity.

The proposed conceptual framework suggests that AI-driven organisational ambidexterity emerges from AI-enabled mechanisms that facilitate both exploratory and exploitative activities. Organisational and contextual conditions, together with AI capabilities, shape how these mechanisms are activated and utilised within organisations. Through the four identified mechanisms, firms could engage in parallel exploration and exploitation activities, which together contribute to ambidextrous outcomes. However, achieving and sustaining this balance is not automatic, as inherent tensions, such as competing priorities and attention fragmentation, may constrain these processes. Overall, the proposed framework highlights that AI enables ambidexterity through context-dependent mechanisms that should be actively managed.

5 Conclusions

This chapter outlines the key contributions of this thesis. First, it describes how the findings of this thesis extend existing research. Second, it reports how the findings could be utilised by senior business leaders, middle-level managers, employees and educators. Lastly, this chapter determines the main limitations of this study and the ways they were mitigated, as well as future research directions.

5.1 Theoretical Contributions

Organisational ambidexterity theory argues that to achieve long-term success, firms must balance their exploratory and exploitative activities (March 1991, 71; Simsek et al. 2009, 867; Kostopoulos & Bozionelos 2011, 387). AI has been shown to impact these activities across fragmented studies (cf. Johnson et al. 2022; cf. Hong et al. 2025; cf. Wang & Zhang 2025). However, existing literature lacks a comprehensive explanation of AI's impact on exploration, exploitation and organisational ambidexterity. Thus, the first contribution of this research is the *integration of the fragmented findings into a coherent conceptual understanding of AI's role in organisational ambidexterity.* More specifically, this thesis extends ambidexterity theory by showing that, in AI contexts, exploration and exploitation are not strictly separated domains. Several AI-enabled processes appear in both exploratory and exploitative domains, particularly in relation to innovation (Lin & Chang 2015, 1195; Al-khatib 2023, 1; Zhang et al. 2025, 1) and learning (Zhang & Luo 2020, 666; Wu et al. 2021, 1389; Waseel et al. 2024, 2116; Callari & Puppione 2025, 5014). This suggests that these two domains, in the context of AI, are increasingly interconnected.

The second contribution of this thesis is the extension of organisational ambidexterity theory by *explaining through which mechanisms AI enables organisational ambidexterity*. Existing studies represent fragmented findings on how AI impacts ambidexterity across various domains. This thesis extends the theory by explaining the collective influence of multiple mechanisms at the intersection of ambidexterity theory and AI. Specifically, this thesis proposes four interrelated mechanisms through which AI enables organisational ambidexterity such as innovation and opportunity recognition, optimisation, learning and knowledge management, and cognitive and analytical mechanisms. Rather than operating in isolation, these mechanisms could jointly shape how AI influences organisational ambidexterity outcomes. These mechanisms emerge from existing but disconnected evidence on AI's role in decision-making (van Rijmenam et al. 2019, 2; Kaur et al. 2019, 49; Alhaimer et al. 2025, 1), learning (Zhang & Luo 2020, 666; Waseel et al. 2024, 2116; Dai et al. 2025, 1), and innovation (Johnson et al. 2022, 7; Callari & Puppione 2025, 5013; Lou et al. 2025, 16), but this thesis integrates them into one framework. This shifts the focus from what AI does to how AI creates value in ambidextrous contexts. These mechanisms may help explain why similar AI capabilities can lead to different organisational outcomes depending on how they are enacted.

The third contribution is the *identification and conceptual structuring of organisational and contextual conditions* that shape the deployment of AI and, consequently, ambidexterity outcomes. Individual studies provide partial insights into which conditions have an influence. For instance, studies show that leadership (Krzywdzinski & Butollo 2022, 179; Solaimani et al. 2024, 445; Waseel et al. 2024, 2115), industry (Plantec et al. 2023, 1; Kronblad et al. 2023, 217; Zhou et al. 2025, 20) and organisational maturity (Kronblad et al. 2023, 217; Khan et al. 2025, 1) impact the usage of AI. However, these conditions are mentioned separately across a large number of studies. This thesis integrates the findings across the studies included in the systematic literature review into one list, showcasing which conditions could have an influence on mechanism activation. This highlights the context-dependent nature of AI-enabled ambidexterity.

Furthermore, this thesis *introduces tensions as a boundary condition to AI-enabled organisational ambidexterity*, representing the fourth contribution. The purpose of the tensions is to add realism to theory to better reflect the complexity of real-world organisational settings. Existing literature outlines separate issues that organisations might experience, such as uncertain financial returns (Gebauer et al. 2020, 29; Giudice et al. 2022, 1), attention fragmentation (Johnson et al. 2022, 10; Hong et al. 2025, 311), and over-reliance on exploitation (Yan et al. 2026, 12). This thesis synthesises a list of tensions, such as uncertain financial returns on AI investments, exploration versus exploitation trade-offs, attention fragmentation, over-reliance on exploitation, and human versus AI role. By compiling a list of tensions, this thesis contributes to the literature by explaining that these tensions may constrain both the activation mechanisms and the achievement of ambidextrous outcomes. This introduces a more nuanced and realistic perspective to ambidexterity theory in AI contexts.

Finally, and most importantly, the key contribution of this thesis is the creation of the *conceptual framework that integrates all identified elements into one model*. As it was mentioned before, existing literature presents valuable but fragmented findings. Drawing generalisable conclusions from individual studies is often challenging. This thesis incorporates the identified conditions, AI capabilities, mechanisms, exploration and exploitation activities, ambidexterity and tensions into one multi-level model. It demonstrates how AI could impact organisational ambidexterity and how this process is shaped by contextual conditions and constrained by inherent tensions. As a result, this thesis moves beyond demonstrating isolated relationships and offers an integrative conceptual explanation of how AI-enabled organisational ambidexterity may emerge.

5.2 Practical Implications

The findings of this thesis provide several practical implications for managers and other stakeholders navigating AI-driven organisational transformations. These implications are particularly relevant for senior executives, middle managers, team leaders, human resource professionals, and operational and project managers. Additionally, the findings may be relevant for educational institutions, industry leaders, technology providers and employees. These implications translate the conceptual framework into actionable insights.

Taking top management and executives into consideration, such as CEOs, CTOs, senior leadership teams and strategy directors, their role is to ensure that *organisations align AI initiatives with both exploratory and exploitative strategic goals, rather than focusing solely on efficiency gains*. This thesis indicates that AI possesses capabilities not only to support efficiency, but also innovation. Firms should consciously decide where they implement AI for exploration and where for exploitation, as over-reliance on exploitation could lead to long-term stagnation. Top management holds responsibility for ensuring the strategic alignment of AI for ambidexterity. This may involve allocating enough resources for experimentation, while maintaining stable processes for efficiency and optimisation. Additionally, managers could regularly monitor the balance and reassess resource allocation when needed to ensure that neither exploration nor exploitation dominates excessively.

Moreover, this thesis showcases that simply integrating AI tools into workflows may not lead to desired ambidextrous outcomes without organisational support. The success of AI-enabled ambidexterity depends on leadership support, organisational culture and employee attitudes. Therefore, middle managers, team leaders and human resource professionals should *actively foster a supportive culture and develop employees' capabilities to use AI for both innovation and efficiency purposes*. For instance, these stakeholders could actively promote a shared vision that encourages both efficiency improvements and experimentation, while also ensuring that organisational structures foster cross-functional collaboration.

Another important implication is related to the four identified mechanisms that enable organisational ambidexterity through AI. Operational and project managers should *design AI-enabled workflows around specific mechanisms, rather than focusing solely on technological capabilities.* AI, on its own, may not directly create value. Instead, this thesis suggests that value is created through the mechanisms. Managers should think about AI and its uses through the lenses of innovation, optimisation, learning and analytical mechanisms. In practice this could mean, designing AI-enabled systems differently depending on the nature of the task. For instance, utilising innovation mechanisms for processes intended to enhance idea generation and utilising optimisation mechanisms for automating certain repetitive processes. Learning and analytical mechanisms could support both exploration and exploitation domains. Thus, understanding and intentionally selecting mechanisms could become a key managerial capability in the context of AI adoption.

This thesis synthesises several tensions that AI implementation introduces. It is crucial that executives, decision-makers and other senior managers *recognise and actively manage these inherent tensions in AI adoption, rather than assuming that technological implementation will automatically lead to optimal outcomes*. The key message is that the tensions in many cases cannot be eliminated but instead must be actively managed. For instance, managers could define clear strategic priorities and governance mechanisms to coordinate activities across the organisation.

Taking broader stakeholder implications into account, educational institutions should *integrate AI and ambidexterity-related competencies into curricula* to prepare the future workforce for ambidextrous thinking and the realities of AI usage. Industry leaders shape the best practices, so *promoting balanced AI adoption strategies* could help other companies follow the similar path. Technology providers, such as firms that develop AI tools, should *develop AI solutions that enable both innovative and efficiency-oriented applications.* Employees, working at organisations involved with AI implementation, are advised to recognise the importance of knowing how to operate AI tools for future career development and encouraged to *experiment with AI beyond routine tasks to unlock its full potential*.

Overall, the findings of this thesis suggest that achieving AI-driven organisational ambidexterity does not solely depend on technological adoption, but rather on active and deliberate managerial process. Organisations that strategically align AI capabilities, organisational conditions and operational practices could be more likely to achieve success in balancing exploration and exploitation.

5.3 Limitations of the Study and Future Research Suggestions

This thesis includes several limitations, which the author aimed to mitigate. Starting with the methodological limitations, this thesis is conducted using systematic literature review methodology, which relies on the interpretation of existing studies, rather than conducting original empirical research. As a result, the findings of this thesis are dependent on the quality of the reviewed articles. To mitigate this factor, only peer-reviewed articles were included in this research from two trusted databases. Additionally, thematic analysis introduces a degree of subjectivity, as the identification and grouping of the themes are dependent on the author's own interpretation. To increase objectivity, a systematic coding method was followed. Furthermore, this research was conducted by a single author, which may limit the reliability of the theme development process. To mitigate this, the thesis was reviewed by two supervisors to increase the reliability of the process.

Regarding the scope and sampling limitations, this research is based on the findings of 71 peer-reviewed articles. Other relevant studies might have been excluded due to database limitations or keyword selection. Additionally, the exclusion of articles written in languages other than English may limit the global representativeness of the findings. However, as the descriptive results of the review indicate, articles from a wide range of industries and geographical areas are included.

As for conceptual limitations, the proposed conceptual framework represents a synthesis of the existing findings, rather than an empirically tested model. Empirical testing would strengthen the validity and generalisability of the framework. Therefore, the relationships between constructs in this thesis should be viewed as conceptual rather than causal.

Taking applicability of the findings into account, the real business world is always far more complex than any conceptual model could accommodate. Even though this thesis aims to add realism to the model by including organisational and contextual conditions, as well as tensions, the findings might not be equally applicable across all organisational contexts. Additionally, the conceptual nature of the framework means that its practical applicability depends on the firms' interpretations of it.

Taken together, these limitations highlight important opportunities for future research to further validate, refine and expand the proposed framework. The main identified future research suggestion is the need to empirically test the proposed conceptual framework. Such research would validate the relationships between constructs and assess their applicability across different organisational contexts. For instance, the relationships between AI capabilities, mechanisms and ambidexterity outcomes could be tested through quantitative methods to assess the strength of the relationships, as well as mediating and moderating roles of the factors. Furthermore, by utilising case study methodology, future studies could explore how organisations implement AI mechanisms in practice. Qualitative research could provide visibility into how organisational contexts shape AI-enabled ambidexterity and more in-depth explanation of the tensions that arise. Additionally, future studies could investigate how exactly organisations manage the tensions, strengthening the depth of the research and providing practical insights. Moreover, longitudinal studies could be particularly useful for examining how AI-enabled ambidexterity evolves over time. For instance, by identifying long-term performance effects and how firms balance AI-enabled exploration and exploitation activities in practice. Lastly, future studies could also focus on specific industries, providing deeper insights into specific contexts of AI-enabled ambidexterity.

Overall, while this thesis is subject to several methodological and conceptual limitations, the author made an effort to ensure credibility, transferability, dependability and conformability. The limitations also highlight the areas that require future research to expand the depth and applicability of the findings. The main suggested direction for future studies is validation and refinement of the proposed framework.

6 Summary

Organisational ambidexterity theory, originally conceptualised approximately 50 years ago, argues that in order to ensure long-term success, businesses need to balance their exploratory and exploitative activities. Existing research shows that artificial intelligence technologies, which have gained popularity in the last decade, could have an impact on organisational ambidexterity. However, existing studies are fragmented and spread across various ambidexterity angles, industries and geographical areas, leaving a research gap in understanding how AI impacts exploration and exploitation on an organisational level. The main research aim of this thesis was to synthesise a conceptual framework that explains how artificial intelligence shapes organisational ambidexterity through its impacts on exploration and exploitation.

Organisational ambidexterity is defined as “the ability to simultaneously pursue both incremental and discontinuous innovation and change” (Tushman & O’Reilly 1996, 24). The main concepts of the theory are exploration and exploitation. Exploration refers to innovation and identification of new opportunities, while exploitation focuses on refining existing capabilities. Artificial intelligence is a technology that can execute cognitive functions that resemble human activities, for instance, learning and problem-solving. Artificial intelligence could be viewed as an internal and external factor influencing organisational ambidexterity. In this thesis, AI represents a contextual lens through which organisational ambidexterity, including exploratory and exploitative activities, are analysed.

In order to fulfil the research aim of conceptual framework creation, this thesis adopts a systematic literature review methodology. 71 peer-reviewed articles were selected from Scopus and Web of Science databases. Data collection followed a rigorous and transparent methodology, including the identification of comprehensive and focused search terms, the use of appropriate operators and screening against inclusion and exclusion criteria. Data analysis followed a hybrid approach – starting with an inductive approach to uncover recurring themes, followed by the application of a broad ambidexterity theory analytical lens to highlight distinctions between exploration and exploitation. As a result, 11 themes were identified belonging either to AI-enabled exploration, AI-enabled exploitation, or AI-enabled organisational ambidexterity analytical lenses.

In the exploration domain, it was identified that AI enables exploratory innovation, sensing and seizing of new business opportunities, and creativity. In the exploitation domain, it was discovered that AI enables efficiency gains, improves the efficiency of business functions, enables exploitative innovation, improves decision-making, and acts as a learning assistant. In the organisational ambidexterity domain, it was uncovered that AI aids in balancing exploration and exploitation, as well as enables ambidextrous learning and innovation. As a final product of this thesis, a conceptual framework of AI-driven organisational ambidexterity was developed. The framework incorporates organisational and contextual conditions, AI capabilities, AI-enabled mechanisms of organisational ambidexterity, exploratory activities, exploitative activities, organisational ambidexterity and tensions, and suggests a conceptual explanation of how these constructs interact. Fundamentally, the framework proposes that conditions and AI capabilities could activate mechanisms that enable both exploratory and exploitative activities, which, in turn, shape organisational ambidexterity. Building on the synthesis of the reviewed literature, this thesis identifies four AI-enabled mechanisms of organisational ambidexterity: innovation and opportunity recognition, optimisation, learning and knowledge management, and cognitive and analytical mechanisms. As an additional layer of realism, the framework highlights inherent tensions that could occur in this process.

The findings of this thesis extend the existing literature in several ways. First, this research integrates the impacts of AI on exploration, exploitation and ambidexterity. Second, it proposes four mechanisms that could explain how artificial intelligence enables ambidexterity. Third, the thesis offers a synthesis of organisational and contextual conditions that influence AI-enabled ambidexterity, expanding existing literature. Fourth, this research incorporates tensions as a boundary condition, adding realism to the theory. Lastly, the key theoretical contribution of this thesis is the proposal of a conceptual framework that integrates all constructs into a single model, illustrating how AI-enabled organisational ambidexterity may arise.

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Zhou, Z. – Liu, D. – Chen, Z. – Pancho, M. (2025) Government adoption of generative artificial intelligence and ambidextrous innovation. *International Review Of Economics & Finance*, Vol. 98.

Appendices

Appendix 1 List of Articles Included in the Systematic Literature Review

Author	Publication Year	Title	Publication Title
Abdullah, H.O.; Atshan, N.; Al-Abrrow, H.; Al Sayed Noor, A.; Valeri, M.; Erkol Bayram, G.	2023	Leadership styles and sustainable organizational energy in family business: modeling non-compensatory and nonlinear relationships	Journal Of Family Business Management
Al-kahtib, A.; Alghababsheh, M.; Khattab, M.	2025	The role of organizational ambidexterity and frugal innovation in enhancing circular supply chains: The effect of artificial intelligence capabilities	Technological Forecasting And Social Change
Al-Khatib, A.	2023	Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework	Technology In Society
Alfarizi, M., Widiastuti, T., & Ngatindriatun	2024	Exploration of Technological Challenges and Public Economic Trends Phenomenon in the Sustainable Performance of Indonesian Digital MSMEs on Industrial Era 4.0	Journal Of Industrial Integration And Management-Innovation And Entrepreneurship
Alhaimer, R.; Alkhaldi, A.N.; Alharbi, E.; Almutairi, B.	2025	Reimagining Marketing Campaigns in Kuwait: A Theoretical Exploration of Digital Transformation Through a Business Intelligence Lens	International Journal Of Business Intelligence Research
Alnofeli, K.K.; Akter, S.; Yanamandram, V.	2025	Unlocking the power of AI in CRM: A comprehensive multidimensional exploration	Journal Of Innovation And Knowledge
Armenia, S.; Barile, S.; Iandolo, F.; Pompei, A.; Sicca, L.M.	2024	Organisational ambidexterity and knowledge management: A systems perspective towards Smart Model-based Governance	Systems Research And Behavioral Science
Callari, T.C.; Puppione, L.	2025	Meaningful work as shaped by employee work practices in human-AI collaborative environments: a qualitative exploration through ideal types	European Journal Of Innovation Management
Cao, H. H., Ma, L., Ning, Z. E., & Sun, B.	2024	How Does Competition Affect Exploration vs. Exploitation? A Tale of Two Recommendation Algorithms	Management Science
Cao, L.; Yang, J.; Chen, Y.-T.	2025	Managing artificial intelligence across functions for enhanced retail firm performance	European Management Review

Chin, T; Li, XY; Caputo, F; Marrone, T	2025	Strategic orchestration of intellectual capital and human resources for AI-driven business model innovation	Journal Of Intellectual Capital
Czyzewska-Misztal, D; Le Bas, C; Thelisson, A	2025	Artificial Intelligence as Enabler of Frugal Innovation: Analyzing the Tensions With Paradox Theory	Strategic Change-Briefings In Entrepreneurial Finance
Dai, J.; Geng, R.; Xu, D.; Shangguan, W.; Shao, J.	2025	Unveiling the impact of the congruence between artificial intelligence and explorative learning on supply chain resilience	International Journal Of Operations And Production Management
Daskalopoulos, E.T.; Machek, O.	2025	Shaping ambidextrous organisations through AI and decision-making: a distinct path for family firms?	Journal Of Family Business Management
de Ruyter, K.; Keeling, D.I.; Yu, T.	2020	Service-Sales Ambidexterity: Evidence, Practice, and Opportunities for Future Research	Journal Of Service Research
Del Giudice, M; Scuotto, V; Orlando, B; Mustilli, M	2023	Toward the human - Centered approach. A revised model of individual acceptance of AI	Human Resource Management Review
Esposito, P; Antonucci, G; Palozzi, G; Fijalkowska, J	2025	Cognitive systems for improving decision-making in the workplace: an explorative study within the waste management field	Management Decision
Fan, H.; Han, B.; Gao, W.; Li, W.	2022	How AI chatbots have reshaped the frontline interface in China: examining the role of sales–service ambidexterity and the personalization–privacy paradox	International Journal Of Emerging Markets
Gebauer, H.; Arzt, A.; Kohtamäki, M.; Lamprecht, C.; Parida, V.; Witell, L.; Wortmann, F.	2020	How to convert digital offerings into revenue enhancement – Conceptualizing business model dynamics through explorative case studies	Industrial Marketing Management
Giudice, M.; Scuotto, V.; Ballestra, L.V.; Pironti, M.	2022	Humanoid robot adoption and labour productivity: a perspective on ambidextrous product innovation routines	International Journal Of Human Resource Management
Gizelis, C.A.; Nestorakis, K.; Misargopoulos, A.; Nikolopoulos-Gkamatsis, F.; Kefalogiannis, M.; Palaiogeorgou, P.; Christonasis, A.M.; Boletis, K.; Giamalis, T.; Charisis, C.	2023	Decision support using AI: the data exploitation at telecoms in practice	Journal Of Decision Systems

Guo, M.; Gu, M.; Huo, B.	2025	The impacts of automation and augmentation AI use on physicians' performance: an ambidextrous perspective	International Journal Of Operations And Production Management
Hartyándi, M.J.	2025	Distrust and disillusionment toward generative artificial intelligence: Psychodramatic exploration of employee trust in organizational technology acceptance	Society And Economy
Hassani, A; Bougadir, H	2026	Responsible digital transformation and sustainable performance: role of organisational ambidexterity	International Journal Of Organizational Analysis
Hiebl, MRW; Pielsticker, DI	2023	Automation, organizational ambidexterity and the stability of employee relations: new tensions arising between corporate entrepreneurship, innovation management and stakeholder management	Journal Of Technology Transfer
Hong, S.; Ryee, H.; Jin, X.; Yang, D.	2025	How Organizations Choose Open-Source Generative AI Under Normative Uncertainty: The Moderating Role of Exploitative and Exploratory Behaviors	Journal Of Theoretical And Applied Electronic Commerce Research
Hong, S.; Zhong, D.; Um, K.-H.	2025	The impact of artificial intelligence (AI) adoption on operational performance in manufacturing	Journal Of Manufacturing Technology Management
Johnson, P.C.; Laurell, C.; Ots, M.; Sandström, C.	2022	Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation?	Technological Forecasting And Social Change
Kar, S.; Kar, A.K.; Gupta, M.P.	2021	Understanding the S-Curve of Ambidextrous Behavior in Learning Emerging Digital Technologies	Ieee Engineering Management Review
Kaur, S.; Gupta, S.; Singh, S.K.; Perano, M.	2019	Organizational ambidexterity through global strategic partnerships: A cognitive computing perspective	Technological Forecasting And Social Change
Khalid, K.; Zamberi Bin Ahmad, S.Z.; Behery, M.	2024	The impact of social ties on balanced vs combined innovation: the role of dynamic capabilities and innovation climate in knowledge-intensive business services firms	International Journal Of Innovation Science
Khan, S.; Khan, K.U.; Mehmood, S.	2025	AI maturity in manufacturing: the role of generative AI in driving organizational performance through exploratory and exploitative innovation	Benchmarking

Kong, HY; Yin, ZH; Chon, K; Yuan, Y; Yu, JH	2024	How does artificial intelligence (AI) enhance hospitality employee innovation? The roles of exploration, AI trust, and proactive personality	Journal Of Hospitality Marketing & Management
Kronblad, C.; Pregmark, J.E.; Berggren, R.	2023	Difficulties to digitalize: ambidexterity challenges in law firms	Journal Of Service Theory And Practice
Krzywdzinski, M.; Butollo, F.	2022	Combining Experiential Knowledge and Artificial Intelligence The Digital Transformation of a Traditional Machine-Building Company	Management Revue
Lee, J.; Kim, D.	2020	Development of innovative business of telecommunication operator: Case of KT-MEG	International Journal Of Asian Business And Information Management
Lee, K.; Woo, H.-G.; Park, T.; de Jong, S.	2023	Managers' Pursuit Of Ambidexterity In The Context Of Artificial Intelligence Implementations: Insights Into Situationally Induced Regulatory Focus	International Journal Of Innovation Management
Lee, V.-H.; Dwivedi, Y.K.; Tan, G.W.-H.; Ooi, K.-B.; Wong, L.-W.	2024	How does information technology capabilities affect business sustainability? The roles of ambidextrous innovation and data-driven culture	R And D Management
Li, J.; Wang, Y.; Zeng, W.; Liang, K.	2025	Impact of AI on firm ambidextrous innovation: Mediating role of digital knowledge coupling	International Journal Of Information Management
Li, J.; Yeo, R.K.	2024	Artificial intelligence and human integration: a conceptual exploration of its influence on work processes and workplace learning	Human Resource Development International
Li, X.; Li, X.; Ding, S.	2024	Effect of knowledge network embedding on exploitative and exploratory innovation: evidence from Chinese advanced manufacturing firms	Technology Analysis And Strategic Management
Li, X.; Qing, L.; Wei, H.; Wei, J.	2025	Artificial intelligence and innovation ambidexterity in advanced manufacturing firms: a knowledge-management perspective	Journal Of Manufacturing Technology Management
Lin, C.; Chang, C.-C.	2015	A patent-based study of the relationships among technological portfolio, ambidextrous innovation, and firm performance	Technology Analysis And Strategic Management
Lin, Y.-K.; Maruping, L.M.	2025	Organizing For Ai Innovation: Insights From An Empirical Exploration Of U.S. Patents	Mis Quarterly: Management Information Systems

Liu, Q.; Du, Q.; Tang, C.; Hong, Y.; Fan, W.	2025	An exploration and exploitation of value cocreation-based machine learning framework for automated idea screening	Decision Support Systems
Liu, Y.; Song, K.; Xu, L.; Song, Z.	2026	ESG and firms’ exploitative versus exploratory innovation: Evidence from a large language model approach	Research In International Business And Finance
Lou, BW; Ma, XY; Wu, LY	2025	Artificial Intelligence, CEO Turnover, and Exploration Orientation in Firm Innovation	Information Systems Research
Lu, Q; Zhou, YH; Luan, ZZ; Song, H	2024	The effect of SMEs' ambidextrous innovations on supply chain financing performance: balancing effect and moderating effect	International Journal Of Operations & Production Management
Lu, XW; Xu, XH; Sun, Y	2025	Enhancing resilience in supply chains through resource orchestration and AI assimilation: An empirical exploration	Transportation Research Part E-Logistics And Transportation Review
Pepple, D.; Muthuthantrige, N.	2026	Artificial intelligence, innovation and the new architecture of exploitation: Towards reconfiguring humanness in the age of algorithmic labour	Journal Of Innovation And Knowledge
Plantec, Q.; Deval, M.-A.; Hooge, S.; Weil, B.	2023	Big data as an exploration trigger or problem-solving patch: Design and integration of AI-embedded systems in the automotive industry	Technovation
Poku, E; Nuertey, D; Agbemude, S; Owusu, F; Buabeng, S	2025	Achieving supply chain resilience through supply chain digitalization: do supply chain ambidexterity and relational governance matter?	Benchmarking-An International Journal
Rashid, A.; Rasheed, R.	2025	Building absorptive capacity and ambidexterity for sustainable manufacturing	Journal Of Manufacturing Technology Management
Rehman, S.U.; Jabeen, F.; Shahzad, K.; Riaz, A.; Bhatti, A.	2025	Industry 4.0 technologies and international performance of SMEs: mediated-moderated perspectives	International Entrepreneurship And Management Journal
Rizomyliotis, I.; Konstantoulaki, K.; Battisti, E.; Do, B.	2025	Start-Up Employees Adoption of AI Technology for Innovation Ecosystems: An In-Depth Exploration	R And D Management
Singh, K.; Chatterjee, S.; Mariani, M.	2024	Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism	Technovation

Solaimani, S.; Dabestani, R.; Harrison-Prentice, T.; Ellis, E.; Kerr, M.; Choudhury, A.; Bakhshi, N.	2024	Exploration and prioritisation of critical success factors in adoption of artificial intelligence: a mixed-methods study	International Journal Of Business Information Systems
van Rijmenam, M.; Erekhinskaya, T.; Schweitzer, J.; Williams, M.-A.	2019	Avoid being the Turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty	Long Range Planning
Wang, S.; Zhang, H.	2025	Artificial intelligence digital employees and sustainable innovation in online retail: The mediating role of ambidextrous green innovation and the moderating role of ethical anxiety	Journal Of Retailing And Consumer Services
Wang, SS; Jia, C; Khan, A; Khan, NH; Hsieh, CH; Hung, CW; Chen, SC	2024	Big Dataanalytics-Artificial Intelligence, Ambidexterity, And Green Supply Chain Management: Implications On Responsible Economy	Rae-Revista De Administracao De Empresas
Waseel, A.H.; Zhang, J.; Zia, U.; Mohsin, M.M.; Hussain, S.	2024	Leadership, knowledge dynamics and dual-path innovation: unravelling the synergy in Pakistan's manufacturing sector	Journal Of Business And Industrial Marketing
Wirtz, J.	2020	Organizational Ambidexterity: Cost-Effective Service Excellence, Service Robots, and Artificial Intelligence	Organizational Dynamics
Wirtz, J.; Hofmeister, J.; Chew, P.Y.P.; Ding, X.	2023	Digital service technologies, service robots, AI, and the strategic pathways to cost-effective service excellence	Service Industries Journal
Witkowski, A.; Wodecki, A.	2024	An Exploration Of The Applications, Challenges, And Success Factors In Ai-Driven Product Development And Management	Foundations Of Management
Wofford, L.; Wyman, D.; Starr, C.W.	2020	Do you have a naïve forecasting model of the future?	Journal Of Property Investment And Finance
Wu, T.; Chen, B.; Shao, Y.; Lu, H.	2021	Enable digital transformation: entrepreneurial leadership, ambidextrous learning and organisational performance	Technology Analysis And Strategic Management
Yan, J.; Husted, K.; Fath, B.	2026	Organizational learning with artificial intelligence: Balancing new tensions between explorative and exploitative learning through hybridization	International Journal Of Information Management
Yun, JJ; Liu, Z; Zhao, XF	2021	Introduction: Ambidextrous Open Innovation in the 4th Industrial Revolution	Science Technology And Society

Zhang, H.; Shah, T.; Ghani, U.; Khan, W.; Ullah, A.; Lew, T.Y.	2025	Plugged in and Powered up: Digital Transformation and Ambidextrous Innovation in Green Supply Chains	Corporate Social Responsibility And Environmental Management
Zhang, Z.; Luo, T.	2020	Knowledge structure, network structure, exploitative and exploratory innovations	Technology Analysis And Strategic Management
Zhou, ZK; Liu, DW; Chen, ZJ; Pancho, M	2025	Government adoption of generative artificial intelligence and ambidextrous innovation	International Review Of Economics & Finance

Appendix 2 NVivo Codebook

Analytical Lenses	Themes	References
AI-enabled exploration (total references = 213)	AI enabling exploratory innovation	148
	AI enabling sensing & seizing of new business opportunities	28
	AI fostering creativity	37
AI-enabled exploitation (total references = 220)	AI enabling efficiency gains	51
	AI improving efficiency of business functions	55
	AI enabling exploitative innovation	51
	Ai improving decision-making	29
	AI as a learning assistant	34
AI-enabled organisational ambidexterity (total references = 62)	AI balancing exploration and exploitation	8
	AI enabling ambidextrous learning	2
	AI enabling ambidextrous innovation	4

Appendix 3 Explanation of the Use of AI

This thesis used ChatGPT tool to change some of the references in the reference list to conform to TSE reference requirements.

Prompt: Fix my thesis reference list. It’s very important that nothing is changed apart from punctuation and styling. Here are the examples [examples of using one, two and multiple authors]. And below is the list to adjust [part of the reference list].

Output: Al-kahtib, A. – Alghababsheh, M.Khattab, M. (2025) The role of organizational ambidexterity and frugal innovation in enhancing circular supply chains: the effect of artificial intelligence capabilities. *Technological Forecasting and Social Change*, Vol. 210. [and others]

Next steps: Outputs were further edited by the author to comply to the reference guidelines.