



PhD thesis

**The impact of Artificial Intelligence focus on firm performance:
the role of R&D and top manager education level**

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**The impact of Artificial Intelligence focus on firm performance:
The role of R&D and top manager education level**

Qiong Yuan

A thesis submitted in fulfilment of the requirement for the degree of
Doctor of Philosophy in Business

Middlesex University London, 2024

ABSTRACT

This study examines the links between the dimensions of companies' focus on artificial intelligence (AI) and firm performance (financial and market performance). AI focus refers to the practice of focusing on specific domains that use cutting-edge technologies enabled by AI to support their operations, realising cooperative development and efficiency improvement between employees and organisations. In addition, the potential mediating role in this relationship between research and development (R&D) staff ratio and R&D investment is examined, and a series of research hypotheses are proposed. Furthermore, the study focuses on evaluating top manager education level as a moderating variable to study the mechanism of AI focus and firm performance.

A panel data estimation approach was employed to empirically test the relationship between AI focus and firm performance to achieve this goal. A rigorous two-stage methodology was implemented. Initial foundations were laid with a careful qualitative synthesis of the existing literature, which helped understand AI focus and how it might affect firm performance. The research used an exploratory approach by analysing the annual reports of Chinese-listed companies for the period 2014 to 2022. This innovative approach offered valid initial data correlating AI focus and firm performance. Finally, the study rigorously validated the proposed model by integrating appropriate financial information and using the sophisticated functionalities of STATA statistical software. This in-depth empirical study enables scholars to confirm their theoretical framework and finds a negative relationship between AI focus and firm performance.

The main contribution of this thesis is to advance knowledge about how companies can capitalise on AI. Firstly, it pioneers the development of AI focus. This multifaceted approach considers how organisations choose to influence and incorporate AI not only into their operations and decision-making but also into their customer interactions. This novel concept is further enriched by categorising AI focus into three distinct dimensions: mechanical, thinking, and feeling AI. This nuanced view reveals the full range of possible organisational AI deployments. Secondly, the study transcends mere definition and discusses the underlying theories of AI focus and the effect on firm performance. It suggests a novel model grounded on the proven economic, dynamic capabilities and talent management theories. The hypothesised negative impact of AI focus on performance is confirmed, which the study argues is based in part on the additional supporting resources devoted to AI, which increase

costs, and on the need for organisational change when AI is introduced. Lastly, the research gives practical advice to businesses that want to develop a strong orientation towards AI. It identifies essential enablers, including employee education and R&D investment, as well as well-focused marketing efforts. This actionable knowledge allows companies to strategically position and optimise their AI focus, assisting them to gain an edge in the competitive reach of AI. Overall, this research contributes significantly to the field of AI and business management. It broadens understanding of AI's focus, reveals its theoretical basis, and offers practical advice to companies trying to harness AI's transformative power.

Keywords: artificial intelligence; R&D; top manager education level; firm performance; longitudinal analysis

DEDICATION

This doctoral research is dedicated to my father, Fuxing Yuan, and my mother, Junxia Shen, whose love and support for me are second to none.

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Contributions to Conference Proceedings – refereed

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AUTHOR'S DECLARATION

I, Qiong Yuan, declare that the ideas, research work, analyses and conclusions reported in my PhD thesis '*The impact of artificial intelligence focus on firm performance: The role of R&D and top manager education level*' are entirely my effort, except where otherwise acknowledged. I also certify that this thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work

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CHAPTER ONE: INTRODUCTION

1.0 Introduction

Artificial intelligence (AI) has been extensively discussed in the literature and applied in real-world contexts. This first chapter provides a summary of this thesis, which explores the relationship between AI focus and firm performance. This chapter begins by discussing the research background in Section 1.1. Then, the research context is provided in Section 1.2, and the research rationale is given in Section 1.3. Following that, the research gaps, objectives and research questions are explained in Section 1.4. Next, Section 1.5 summarises the key findings and research contributions. Then, Section 1.6 summarises the research gap and necessity. Finally, Section 1.6 presents the structure of the thesis.

1.1 Research background and motivation

The fast development of AI is a striking achievement in today's world. In fact, in recent decades, AI technology has played a significant role in the rapid development of contemporary society. Mainly since the invention of ChatGPT in 2022, AI has fundamentally changed people's way of life and work. In a short period, AI has evolved to become an integral part of society (Roser, 2022). The rapid development of AI has generated a false impression that the technology has existed for quite a long time. However, it is remarkable to imagine that it was developed no more than a few decades after the Second World War, which is illustrated in the following Figure 1.

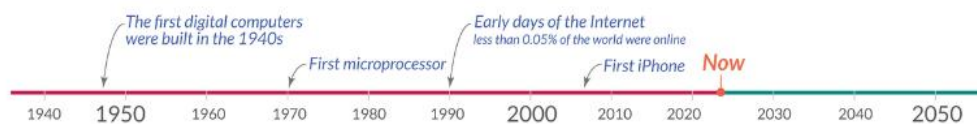


Figure 1. Milestones of AI development (Roser, 2022)

Over the years, with the continuous advancement of AI technology, more and more enterprises have begun to pay attention to and adopt AI. Different institutions and organisations focus on and choose different AI technologies according to their own needs. Several questions, therefore, arise, such as “What is the current focus of listed companies on AI?”, “What is the definition of AI focus?” and “Does having a focus on high-tech AI affect the performance of listed companies?” These issues are worth exploring. The level the world has reached in modern technologies allows people to introduce necessary managerial and

organisational innovations, and AI technology is one such model. Today, AI has gained momentum and attention as a cutting-edge technology. It is one of the most powerful technologies available, capable of revolutionising the business world and society at large (Lui *et al.*, 2022). It will transform every aspect of the market through the augmentation of intelligence (Davenport *et al.*, 2020; Rust, 2020). Projections suggest that 2030 AI will generate about \$13 trillion in economic output and create between \$1.4 and \$2.6 trillion in market value (Chui *et al.*, 2018; Mishra, Ewing Cooper, 2022). Because of the greater acceptance of technological innovations in society, AI is developing at an unprecedented pace and has been used in many industries. For example, it can be applied in various fields, such as optical communication, network planning, transportation networks, after-sales service and medical science (Alzaidi, 2018; Wang *et al.*, 2021a). Different AI technologies, including automation and machine learning, have been successfully utilised by organisations to reduce errors, streamline business processes and improve resource allocation. Moreover, AI has often been associated with innovation and sustainable competitive advantage in different businesses. Organisations frequently utilise these technologies to oversee their R&D, strategic decision-making and product innovation, thus contributing to their longevity and competitiveness in dynamic markets.

There is a large body of literature attempting to understand the impact of AI technology on firm performance, emphasising the complexity of measuring AI focus and investment returns (Mishra, Ewing and Cooper, 2022). The introduction of AI into organisational operations heralds a new set of barriers and challenges (Duan, Edwards and Dwivedi, 2019), which have led some scholars to directly examine AI's role in influencing firm performance. Mishra, Ewing and Cooper (2022) examined the links between firms' focus on AI and their gross and net operating efficiency. Luo (2022) suggested that using AI was one primary method that corporations used to improve the efficiency of their enterprise network innovation and, furthermore, to achieve improved performance. Wamba-Taguimdje *et al.* (2020) studied how AI influenced firm performance by examining the business value of AI-based transformation projects. It is a challenge for corporations to successfully apply AI because they fail to improve the value of the business unless firms can successfully incorporate AI into their ecosystems to support their operations. Liu *et al.* (2022) studied the impact of AI on corporate value by studying 119 announcements based on 62 listed companies investing in AI. It was found that investment in AI had a negative effect on company market value and that

non-manufacturing companies and companies with weak information technology (IT) capabilities or low credit ratings were more negatively affected. By summarising a large number of studies from recent years, it was found that they had not yet reached a consensus on the scope and measurement standards of AI focus (see Appendix 1, Overview of AI literature review). It is important to understand the meaning of AI focus and establish its exact definition in this thesis. Drawing on a large body of literature, this study defines AI focus as the concentration on specific domains that utilise cutting-edge technologies mirroring human capabilities and adopting human-like intelligence (see Albrecht, Rausch and Derra, 2021; Chukwudi *et al.*, 2018; Fukuzumi *et al.*, 2019; Mishra, Ewing and Cooper, 2022; Wamba-Taguimdje *et al.*, 2020 among others).

Although the adoption of AI is of unparalleled importance to the competitiveness of enterprises, it remains a significant and costly challenge for them, and the results of its impact remain ambiguous (Agrawal, Gans and Goldfarb, 2018; Li *et al.*, 2019; Caputo *et al.*, 2019; Alekseeva *et al.*, 2020; Said and Sheng, 2020; Liu *et al.*, 2020; Haenlein and Kaplan, 2021; Liu *et al.*, 2022). The overall adoption rate of AI by enterprises is still very low, partly due to a lack of professional knowledge, insufficient technical logic infrastructure, high perceived complexity and questionable results (Balakrishnan and Dwivedi, 2021; Lui *et al.*, 2022; Mishra Ewing and Cooper, 2022). It is currently unclear whether the returns on investment in AI exceed the costs (Bock, Wolter and Ferrell, 2020; Makarius *et al.*, 2020). Firm performance is at the core of determining the cost-effectiveness of AI, as good efficiency will affect tomorrow's firm performance. Therefore, this study explores the relationship between a company's AI focus and its total asset return rate and Tobin Q value, as these measures ultimately determine firm performance. Therefore, based on the previous management literature and economic theory, a guiding framework was developed to demonstrate how AI focus affects the performance of enterprises. Then, panel data were used to test the relationship between AI focus and firm performance. The research provides timely and detailed empirical insights into corporate strategies for focusing on the impact of AI technology.

1.2 Research context

AI research is a comparatively new academic field since the technology has only recently exploded and expanded to influence firm management. So far, much of the attention of the literature on AI, as far as firm management is concerned, has been paid to how the

technology helps to enhance firm capability and performance for effective competition. By reviewing the literature (*Table 2.8*), it can be seen that some research has studied the relationship between AI adoption and firm performance (e.g. Agrawal, Gans and Goldfarb, 2018; Alekseeva *et al.*, 2020; Lui *et al.*, 2022). Nevertheless, there are mixed results regarding the relationship between AI adoption and firm performance. Some studies reveal a positive relationship, while others demonstrate a negative relationship. Moreover, the AI-related literature has probed the factors that influence AI adoption and firm performance, such as the ratio of R&D staff as well as the educational level and personal competence of senior executives of firms. As demonstrated by Chen, Esperanca and Wang (2022), despite the significant potential of AI technologies in enhancing firm performance, the existing literature often overlooks aspects such as firm creativity, artificial intelligence management (AIM), and artificial intelligence-driven decision-making (AIDDM) in the interplay between these factors. The dynamic shifts within the business environment can impact the utilisation of digital technologies, including AI (Bag *et al.*, 2020), and subsequently influence firm performance (Chen, Esperanca and Wang, 2022). The innovation-focused organisational culture marked by the rising status of R&D emerges as a critical factor influencing firm performance (Yildiz and Aykanat, 2021). Moreover, senior managers' education level influences their expertise and experience in understanding market dynamics, including technology developments (Cameiro, 2000). Marketing expenditure refers to the total amount of money or energy devoted to marketing purposes within an enterprise, and its contribution to AI is considered to be significant to enhance brand recognition and reputation (Palanivelu and Vasanthi, 2020). Nevertheless, there is a scarcity of studies incorporating sufficient moderating variables related to R&D and managers' education levels to elucidate the connection between AI focus and firm performance. Therefore, considering the changeable nature of markets, it is essential to explore the impact of AI's focus on firm performance, with consideration of the role of R&D and the education level of top managers. This will offer more practical insights for practitioners to guide their real-world strategies and practices.

As AI continues to be more widely applied with different scopes, its ethical and legal implications have been discussed in social research (Cath, 2018), while computer science has developed advanced deep learning algorithms (LeCun, Bengio and Hinton, 2015) and business management scholars have studied its impact on customers, markets, companies and stakeholders in an increasingly automated and interconnected business world (Huang and

Rust, 2018). AI is defined as “a branch of computer science, and AI systems think and act like humans. It is broadly divided into two parts: automation and augmentation. Automation means machines take over human tasks, while augmentation means humans work closely with machines to perform tasks” (Alzaidi, 2018; Fukuzumi *et al.*, 2019; Mishra, Ewing and Cooper, 2022). According to Cath (2018), AI has been widely implemented in different spheres, including the supply chain, retail, service and advertising industries. Although researchers widely agree that AI is of unparalleled importance to the competitiveness of companies, it is a vast and expensive challenge for companies, and the benefits of this effort may not be clear-cut (Agrawal, Gans and Goldfarb, 2018; Haenlein and Kaplan, 2021; Lui *et al.*, 2022).

Thus, from the prior research, it can be summarised that while researchers widely agree on the crucial importance of AI technology for companies' competitiveness, AI also poses a significant and costly challenge. The benefits of efforts to introduce it may not be straightforward. There is controversy regarding the impact of AI use on companies' market value, with some studies finding no impact at all (Saide and Sheng, 2020), such as Lui *et al.* (2022) arguing that AI investment could negatively affect companies' market value, while other researchers such as Agrawal, Gans and Goldfarb (2018) believe that with the use of AI technology, companies can benefit from economies of scale and reduce costs. This use of AI will help employees improve workplace efficiency, produce more products at the same time, reduce production costs, and promote performance growth. However, there is a knowledge gap in AI's impact on business value because scholars have conflicting findings. Therefore, further research is required to examine the issue more precisely and more comprehensively.

Regarding the significant focus of AI research, different previous studies have focused on different issues. For instance, Caputo *et al.* (2019) explored the role played by an individual's soft skills and Big Data management in enhancing a firm's performance. The study reveals that even though firms are already exploring the option of applying soft skills to Big Data management, the connection between Big Data, BPM and AI is considered one of the most controversial debates. On the other hand, Liu *et al.* (2020) focused on AI's influence on technological innovation. The study, which depends on information obtained from panel data from China's manufacturing sectors, reveals that the higher level of AI seen in the technological sector improves the level of innovation. Another study on implementing AI in other industries focused on large bio-pharma firms to explore AI's impact on drugs (Lou and

Wu, 2021). The study contends that implementing AI in the drug manufacturing industry has advantages and disadvantages. The study reveals that while AI aids the effective execution of specific drug manufacturing innovations, it does so at the risk of permitting specific undesirable drug characteristics. Such drugs tend to affect human health negatively, thus failing the test for their purpose. Consequently, pharmaceutical firms may develop a bad brand reputation, making them less likely to win a huge market segment. In an effort to evaluate the influence of AI focus on firm performance, another study focused on the theory of IT capabilities to critically evaluate how this was achieved at the organisational and process levels (Wamba-Taguimdje *et al.*, 2020). The study suggests that applying AI is vital for firm performance since it covers a broad spectrum that is essential to business operations. For instance, AI can be applied to chatbots, machine translations and self-learning algorithms, giving individuals the best platform to analyse their environment and act based on the situation. However, while this suggests AI focus is essential to transformation efficiency and technology innovation, it is not clear from the literature whether AI focus necessarily leads to improved firm performance, given the presence of other factors such as increased costs, operational changes, etc.

1.3 Research gap and its importance

The knowledge gap regarding the impact of AI focus on firm performance relates to the fact that increased focus on AI has the potential to change the way companies operate. The level of attention paid to AI will be affected by a company's AI adoption rate. For enterprises, successfully applying AI is a challenge because if enterprises cannot integrate AI sufficiently well into their own ecosystems to support their operations, they will not be able to increase their business value. A large body of literature was reviewed; for example, Caputo *et al.* (2019) pointed out the strong relationship between employees' personalities and companies' economic performance when applying Big Data to guide their work. Detailed analysis shows that in addition to the R&D investment that companies make to promote Big Data, employee personalities also influence how effectively employees adopt AI technology to achieve organisational tasks and performance. Li *et al.* (2019) classified enterprises into four categories based on different business models and available AI technologies, indicating that the adaptability between business models and AI technologies is the most critical factor in building ecosystems and improving operational ecosystems in order to obtain competitive advantage. The study's findings suggest that companies using AI technologies to improve

performance should establish a decision-making system that coordinates corporate strategy, available resources, and alternative AI technologies from which they can choose. Lee, Kwon and Pati (2019) showed that R&D investment and operational excellence were the two most important factors leading to improved corporate performance when the researcher understood environment-facing corporations based on the analysis of historical data.

A significant relationship between AI and firm performance was noted after summarising a large amount of literature (Table 2.8). Since the development and successful implementation of AI require technological R&D investment, a large number of R&D talents, as well as the commitment of top management to support the company's AI technology, several critical research gaps were identified. This study examines the comprehensive relationship mechanism between AI focus and firm performance using the indicators of R&D investment and the ratio of R&D staff as mediating factors and senior managers' highest education level as a moderating factor. In the current literature, much attention has been paid to how AI has impacted firm performance. However, there is no or very little focus on the managerial dimension of AI's impact on firms, such as the R&D staff ratio and level of education of senior executives in China. These limitations suggest that the previous studies failed to examine the significant impacts of AI focus on the operations and performance of firms from various perspectives or to discuss the relationships with firm performance defined from different perspectives. For example, previous studies failed to identify how the market indicator measured by Tobin's Q is related to the financial indicator measured by ROA, with AI as a supporting technique that influences the operational functions of corporations. In-depth analyses of how AI's focus in corporations influences the various aspects of management practices could be conducted at different levels and in terms of the firm's performance. For example, the dissertation studies how the firm's operation is related to financial indicators measured by ROA because improved operational efficiency is always related to improved firm performance, assuming other factors are constant (Gandin and Cozza, 2019). It also considers short-term performance evaluations, such as financial performance, and long-term performance evaluations of market performance.

Previous studies have not conducted in-depth analyses of the mechanisms of how AI is related to firm performance, with R&D as the mediator. Some studies have referred to R&D to examine their roles in technological advances, such as by investing in AI, to achieve improved firm performance; however, the previous studies have not identified a precise

mechanism by which R&D acts as a mediator between AI focus and firm performance. Some studies have suggested an overall positive effect of AI on performance. For example, Luo (2022) indicated that AI helped improve customer values, resulting in improved financial performance. Liu *et al.* (2020) confirmed that AI influenced technological innovation by significantly impacting employees' work efficiency. Zhao *et al.* (2021) suggested that R&D investment could improve organisational innovation performance by enhancing innovation knowledge. Wamba-Taguimdje *et al.* (2020) indicated that AI helped improve employees' capabilities because adopting AI provided opportunities to strengthen their ecosystem's efficiency and optimise their strategic and competitive advantages, with improved automation, information and transformation effects. Lee, Kwon and Pati (2019) concluded that R&D investment and operational excellence were the top two factors leading to improved performance in corporations when the researchers could understand the environment facing corporations based on the analysis of historical data. This dissertation combines findings from previous studies to try to identify a mechanism by which empirical studies could be constructed by including R&D investment and R&D staff ratio as the moderators to study the impacts of AI focus on firm performance because improved R&D investment and R&D staff ratio mean better value for customers, the improved technological capabilities of employees and enhanced capabilities in auditing and responding to future challenges based on historical data (Xu and Zeng, 2021), but these combined factors may still have an overall negative effect on firm performance given the additional costs and organisational changes associated with AI application.

Firms' ability to develop and utilise innovative capabilities is crucial for achieving competitive advantage and performance. Given the increasing level of competition and declining product lifecycles, firms' ability to generate continuous innovations, enabling them to develop and maintain competitive advantage, may be more critical than ever. Accordingly, firms may need to devote more effort and resources to R&D activities than in the past. They can develop their technical capabilities, provide economic rent, and acquire first-mover advantages through R&D activities. This contributes to firm performance (Bowen, Rostami and Steel, 2010). In a highly competitive business environment, R&D can help companies launch new products and increase customer satisfaction etc., thus affecting corporate performance (Ruiqi *et al.*, 2017). However, previous research has not conducted an in-depth analysis of the relationship between AI focus and firm performance mediated by R&D. This

paper uses R&D investment and R&D staff ratio as intermediaries to construct an empirical study to study the impact of AI focus on firm performance, since the more employees there are in the R&D department, the more talents will be available to support business operations to quickly adopt AI in operations (Xu and Zeng, 2021).

However, before benefiting from AI, companies face the challenge of identifying key areas relating to AI (Alekseeva *et al.*, 2020), such as whether the company has determined what problems the AI will solve, what data are needed for the algorithms used in the AI technology, what expertise is required to supplement the company's AI, how to use the output of the algorithms to make decisions the company needs to make, etc. These are some of the fundamental questions for successful AI implementation and are usually addressed by employees at a management level. AI development and successful implementation require top management support for the company's AI technology. Senior executives, as leaders and decision-makers of an enterprise, determine the development direction of the enterprise to a large extent. Most previous literature explores the relationship between executive education level and firm performance. The empirical literature has not examined the role of managers in focusing on AI and ensuring the benefits of AI deployment for firm performance. Moreover, previous research has not conducted an in-depth analysis of the relationship between AI focus and firm performance with EDU as a moderator. Therefore, this paper uses the educational level of top managers as a variable to study the moderating role it plays in the relationship between AI focus and firm performance.

1.4 Research objectives, research questions and rationale

As discussed above, there are several significant gaps in the literature relating to the effect of AI focus on firm performance. Extensive research is needed to determine the correlation between AI focus and corporate success, especially in the setting of public corporations. Furthermore, it is imperative to comprehend the variables impacting the adoption of AI, with a particular focus on the moderating or mediating functions of senior managers' educational attainment and organisational R&D capacities. Additionally, the ever-changing nature of the corporate environment and the need for an innovation-driven organisational culture are critical elements requiring additional research.

Given the importance of AI focus, this study examines how a company's AI focus can impact firm performance among the relevant key performance indicators. Furthermore, the term

“firm performance” describes a multifaceted and comprehensive concept. Some errors can occur when analysing it through only a single lens. To rectify the defects of single-lens measurements, this study opts for a dual approach, incorporating both accounting and market indicators to provide a more holistic reflection of the firm's intrinsic performance, namely, one accounting indicator (return on assets (ROA)) and a market indicator (Tobin's Q ratio). However, it is still unclear whether investing in AI will yield a greater return than it costs; thus, it is critical to comprehend the relationship between a company's AI emphasis and firm success and establish essential performance metrics. The growing range of sectors utilising AI highlights the necessity to analyse its effects thoroughly. Thus, more study is necessary to close these gaps and offer valuable insights for real-world strategies and practices. Hence, this research aims to empirically examine the impact of AI focus on firm performance and to explore the role of R&D and senior managers' education level in the relationships between AI focus and firm performance.

Specifically, the research aims will be obtained through four precise objectives, as follows:

1. To understand the nature of AI focus.
2. To investigate the relationship between AI focus and firm performance.
3. To analyse the moderating role of top manager education level (EDU) on the relationship between AI focus and firm performance.
4. To examine the mediating role of R&D staff ratio and R&D investment in the relationship between AI focus and firm performance.

Of the above objectives, the first is intended to be achieved by reviewing the previous literature and relevant documents, such as specific financial reporting standards for measuring intangible assets. At the same time, the final three require undertaking independent empirical research using regression analysis methodology.

In the work of this study, the aim is to address the following research questions:

- RQ1. What is the AI focus, and how has it been developed to influence firm management?
- RQ2. What are the key influences of AI focus on firm performance?
- RQ3. What is the moderating role of top managers' education level in the relationship between AI focus and firm performance?

RQ4. What is the mediating role of the R&D staff ratio and R&D investment in the relationship between AI focus and firm performance?

1.5 Expected contributions

This study is expected to contribute to the theoretical research of business behavior in the context of the development of AI. Its contribution first lies in supplementing existing management theories related to the application of new technologies. As is well known, AI technology is a high-quality resource, but this research not only considers its resource advantages, but also comprehensively understands the impact of a company's AI on its financial and market performance from three perspectives: Economic Theory, Dynamic Capabilities Theory, and Talent Management Theory, starting from a series of complex situations such as enterprise management and operational processes. This study contributes to enriching theoretical thinking on the details of management dimensions. Studying the impact of AI focus is of great significance for helping enterprise managers design important decisions for development strategies by using AI technology to evaluate value from the perspective of asset returns. This study helps business managers refine management stages such as concept formation, development design, and evaluation implementation. This study also helps to gain a deeper understanding of the relationship between AI focus and firm performance by identifying the main risks or challenges that businesses face when adopting AI technology.

The research presented herein significantly advances our understanding of the relationship between firm performance and AI focus, addressing critical gaps in existing literature. As organisations increasingly adopt AI technologies, it is crucial to comprehend their impact on financial and market performance to guide strategic decision-making (Lee *et al.*, 2022). This research broadens its scope by evaluating mediating factors such as the R&D staff ratio and investment in R&D. These metrics are vital to organisational strategy, influencing how AI initiatives translate into tangible business outcomes. Understanding these mediating mechanisms provides deeper insight into the interplay between internal processes and firm performance. Moreover, the inclusion of top manager education level as a critical factor adds depth to the research. Managerial education significantly impacts the strategic implementation of AI initiatives, support, and understanding. This approach offers a comprehensive perspective on the human element in AI integration, with practical implications for leadership development in the evolving digital landscape. Additionally, this

research has substantial implications for policy and industry standards. As AI focus continues to reshape industries, insights from this study can inform guidelines for responsible AI implementation, addressing transparency, ethical considerations, and leadership roles in AI-driven strategies (Binns, 2018; Floridi *et al.*, 2018).

From an empirical perspective, this thesis contributes notably by developing the concept of AI focus—a multifaceted approach examining organisational AI integration across operations, decision-making, and customer interactions. This concept is enriched by categorising AI focus into mechanical, thinking, and feeling dimensions, offering a comprehensive view of AI deployments within organisations (Huang & Rust, 2018; Mishra *et al.*, 2022). While grounded in existing literature, this study extends the application of these concepts by focusing on data from China (2014-2022), providing fresh empirical evidence of the relationship between AI focus and firm performance using metrics like ROA and Tobin's Q ratio. Overall, this research contributes significantly to the field of AI and business management. It provides a broad understanding of AI's focus. It reveals its theoretical basis, as well as offers practical advice for companies that are trying to harness the transformative power of AI. It provides additional evidence of the relationship between AI focus and the performance of the enterprises that are listed on the Chinese stock market. Compared to other relevant studies (e.g. Mishra, Ewing and Cooper, 2022), the current work focuses on data analysis in China from 2014 to 2022. It includes the above outcomes (ROA and Tobin's Q ratio). This paper first discusses the theoretical background and hypothesis development in the following sections. Then, the potential methods are presented. The paper concludes with possible implications and future research directions.

1.7 Structure of the thesis

The thesis is divided into eight chapters. Chapter 1 is an introductory chapter that introduces this research's overview, importance, and motivation. This chapter also identifies the research objectives and the study's original contribution to the body of knowledge. Chapter 2 details the relevant theories and general literature on AI focus and firm performance, especially economic theory, dynamic capabilities theory (DCT) and talent management theory (TMT), to empirically answer the research questions raised in Chapter 1. Chapter 3 provides a review of China's AI policy. It provides an in-depth understanding of China's AI policy development and AI economic reforms, as well as criticism of Chinese companies' focus on and application of AI technology systems. Chapter 4 presents the conceptual framework and

hypotheses, developing the framework based on the literature on the impact of AI and firm performance. This chapter combines relevant theories to support the relevant empirical research on AI and its impact on corporate finance. Chapter 5 details the methodology and content adopted in the study, covering the research design, research sample, data collection methods, model specification and definitions of the variables. Chapter 6 analyses the techniques used in the statistical data and the results of the empirical analysis. Specifically, this chapter discusses the empirical results in the following aspects: (i) the direct impact of AI focus on the performance of Chinese listed companies, (ii) the mediating effect of the R&D staff ratio on the relationship between AI focus and firm performance, and (iii) the moderating effect of top manager education level on the relationship between AI focus and firm performance. Chapter 7 discusses why the empirical results were produced and analyses the reasons for the findings. Chapter 8 summarises the main research results of this paper and its contributions to academia and practitioners. This chapter also points out the study's limitations and provides suggestions for future research directions.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter provides a literature review of the prior findings by scholars on the research topic of AI focus and firm performance. The theoretical background is reviewed in Section 2.1 and AI focus and firm performance are reviewed in Sections 2.2 to 2.5. In the section on the theoretical background, economic theory, DCT, and TMT are reviewed. The later sections review the core concepts in the domain of AI focus and firm performance. Then, Section 2.6 provides a literature review on the role of R&D and executive education. Following that, a summary of key definitions and concepts is provided in Section 2.7. Section 2.8 provides an overview of the chapter.

2.1 Theoretical background

2.1.1 Economic theory

By nature, economic theory is an umbrella term involving different types of models and frameworks suited for different socio-economic circumstances. In business development, economic theory falls into categories of management theories targeted at drawing theoretical principles to guide the rational behaviour of a firm (Kahneman & Tversky, 1979). Economic theory helps to provide a big picture of planning by business managers to avoid notable risks of deviation from the planned management track. In the economics of firm management, these principles are based on assumptions derived from the summarisation of actual management behaviour and lessons derived by managers (Gilboa *et al.*, 2022). Practically, the assumptions are about crucial variables of firm management such as costs, profits, investments, capital, business forecasting on a long-term and short-term basis and so forth (Org., 1998). Of course, different branches of economic theories may derive from different variables above. For example, economists often take serious consideration in cost control, which helps to generate the cost control theory targeted at identifying, analysing and eliminating unnecessary expenses to ensure reliable profits. Hence, prudent thinking and management models are based on this theory (such as the lean management practice created by Toyota in the 20th Century, which targeted lean thinking in cost control). The economic theory within firm management is usually known as managerial economics, which is understood or defined as a field of study focusing on microeconomic factors influencing the strategic decision-making by firms. These decisions are usually crucial in impacting a firm's

profitability, implying that companies should be prudent and cautious when making these decisions (Jeffery *et al.*, 2017). Ultimately, the principles of managerial economics are intended to produce positive outcomes for firm management with rational strategies.

Adopting AI is an essential decision of a firm, which, according to Wilkinson (2022), creates a new ecosystem within a company, implying new problems and profound changes influencing the normal way of firm operations. According to managerial economics, new strategies are required to cope with the change. Cost control is a strategy that, according to managerial economics, is the process of identifying and reducing management expenses to ensure firms' profitability (Fahyan, 2011). Ideally, cost control starts with rational budgeting and ends with firms improving efficiency. Practically, cost control is an important strategy to achieve rational business actions based on rational forecasting of the consequences of actions relevant to the safe operations of businesses as far as business resources are concerned (Fudenberg & Levine, 1994). Based on cost control, a company needs to do the following when making important decisions for actions.

1. **Setting the goal.** This step determines what should be included in the cost management plan, which might conflict with the interests of different stakeholders.
2. **Resource estimation and planning.** In this step, businesses need to estimate and calculate the resources (especially financial resources) required to complete a project.
3. **Cost control.** This phase includes all the actions taken by a business to control costs. In particular, this process involves plans to reduce waste and estimate the potential risks arising from the excessive use of business resources to balance business safety and the necessity of development.

Overall, cost control is an essential strategy under the framework of economic theory. It involves all the actions a business takes to control unnecessary expenses. Especially cost control process involves plans to reduce waste and estimate the potential risks arising from excessive use of business resources to balance business safety and necessity of development (Baye & Bloomington, 2006). It helps to generate a crucial principle of firm management derived from the economic theory of firm management. Thus, economic theory and related principles remind individual firms to have scientific planning in business operations associated with significant changes caused by adopting new technologies and other critical change management (Douglas & Callan, 1992).

To summarise, economic theory calls for cautious decisions when a business launches necessary actions for strategic change since these decisions often impose crucial changes and perceived risks. The theory generally reminds businesses to reduce overspending, plan effectively, facilitate financial health, mitigate risks and improve visibility or transparency when adopting important decisions (Mattick, 2011).

2.1.2 Dynamic capabilities theory

Dynamic capabilities (DCs) refer to a company's capacity to effectively incorporate, construct and adapt internal and external resources and competencies to navigate and influence swiftly evolving business landscapes (Teece and Pisano, 2003). The primary objective is to yield exceptional returns. While DCs may be grounded in specific procedural changes (for instance, following established paths in product development) and scrutiny (such as evaluating investment options), they more frequently originate from inventive managerial and entrepreneurial endeavours (like venturing into novel markets). These capabilities mirror how promptly and to what extent a company's distinctive resources and competencies can be harmonised and adjusted to align with the opportunities and demands of the business environment (Teece, 2010). A company endowed with robust DCs stands a chance of attaining extraordinary returns because markets often undervalue them concerning their significance to the buyer, particularly when the buyer possesses supplementary and specially matched assets. The fundamental nature of resources/competencies and DCs is that, in most cases, they cannot be simply purchased; instead, they need to be developed. Therefore, DCs indicate the ability to adjust and readjust as resources and competencies are fused and refashioned to align with the business environment (Teece, 2010). The distinctive skills of sensing, seizing and transforming are crucial characteristics of firms, which empower them to adapt and coevolve in tandem with the business environment. These capabilities play a pivotal role in ensuring sustained long-term profitability.

Dynamic capabilities theory (DCT) emerged as an alternative framework to address some of the limitations inherent in RBV theory (Bhardwaj and Srivastava, 2021). DCT introduces path-dependent processes that empower firms to navigate rapidly changing environments by constructing, integrating and reconfiguring their portfolio of resources and capabilities (Salvato and Vassolo, 2018). Originating from RBV theory (Wernerfelt, 1984), DCT sought to overcome the shortcomings of explaining sustainable competitive advantage and superior performance in dynamic settings. Teece (2007) significantly advanced DCT by delving into

the micro-foundations of three dimensions: sensing (identifying and assessing opportunities), seizing (mobilising resources to address opportunities and capture value) and transforming (continuously renewing and reconfiguring the business firm's intangible and tangible assets). However, the theory has faced substantial criticisms, including challenges in defining the term itself and assessing the outcomes of the theory (Bleady, Ali and Ibrahim, 2018), difficulties in understanding the nature of DCs and the absence of precise models for measuring these capabilities and their impact on organisational performance (Baia and Ferreira, 2019). Criticisms also revolve around the theory being perceived as repetitive (Eisenhardt and Martin, 2000) and inadequate in offering a comprehensive understanding of how DCs function (Schreyogg and Kliesch-Eberl, 2007)—a lack of clarity regarding core concepts further plagues DCT (Vogel and Guttel, 2013).

Thus, DCT is valuable in its essence, but in the application process, it is essential also to be aware of the limitations reviewed above. Overall, this study employs economy theory (Gilboa *et al.*, 2022; Kahneman & Tversky, 1979; Org, 1998), DCT (Eisenhardt and Martin, 2000; Teece, Pisano and Shuen, 1997; Collis, 1994) and TMT (Greene, 2020; Soheli-Uz-Zaman *et al.*, 2022; Davies and Kourdi, 2010) to explore the correlation between AI focus and firm performance. In the contemporary globalised, intricate and constantly evolving business landscape, the challenge for enterprises to endure has intensified. Rapid technological disruptions and intense competition from nations like the United States and India necessitate swift business responses. The dynamics and intricacies of today's technology competition pose challenges for companies sustaining their competitive edge.

2.1.3 Talent Management Theory

Talent management, a crucial aspect of strategic HR, involves recruiting, retaining, developing, rewarding and optimising the performance of individuals within an organisation (Acar and Yener, 2016). Companies practising talent management demonstrate a strategic and intentional approach to various human resource management (HRM) aspects, including sourcing, attraction, selection, training, development, retention, promotion and employee mobility throughout the organisation (Stahl *et al.*, 2012). Some studies (e.g. Mueller, 1996; Clardy, 2008; Vaiman *et al.*, 2021) highlight the evolving role of HR as a unique and differentiating asset that plays an increasingly vital role in organisations. Talent management, considered a paramount function of strategic HRM, underscores the significance of human capital as the most valuable resource for a company (Dorasamy, 2021). Strategic

implementations focus on identifying and nurturing bright and promising employees, recognising that talent management extends beyond discovering and developing abilities (Greene, 2020; Soheli-Uz-Zaman *et al.*, 2022). It also involves facilitating the progression of talented employees within the organisation, allowing them to showcase their potential and abilities. Therefore, it can be inferred that while talent management activities encompass various human resource functions such as recruitment, selection, hiring, development and rewarding, each activity has distinct nuances and focuses.

The field of talent management has experienced rapid growth, leading researchers to debate and discuss its theoretical boundaries. The concept of “the war for talent”, introduced by McKinsey consultants, has fuelled discussions and debates since the 1990s (Kinsella, 2022). Global organisations face challenges in talent management activities to navigate the complexities of global competition (Harsch and Festing, 2020). Specifically, scholars have also classified different types of talents in organisations. At the pinnacle of this classification are leadership talents, representing individuals tasked with the development, preparation, delivery and execution of corporate-level strategies (Alsakarneh and Hong, 2015). Another crucial category comprises essential talent, i.e. individuals with a solid competitive spirit valued for their capabilities, vision, and future-orientated perception, making them vital contributors to the organisation (Kwon and Jang, 2022). Substantial talents form a workforce powerhouse responsible for final product delivery to consumers, emphasising their critical role in production (Davies and Kourdi, 2010). Lastly, supportive talents play a crucial role in activity implementation by supporting non-core business functions. These roles often involve administrative activities, some of which may be suitable for automation (Davies and Kourdi, 2010). The systematic classification of talents allows organisations to strategically manage and harness their workforce's diverse skills and contributions. One of the crucial factors influencing senior leaders' talent capabilities in implementing tasks is their level of education (Wiblen and Marler, 2021). Leaders with a higher education level tend to be more professional in handling issues and leading people based on a widened mindset and more proficient skills (Murphy and Reichard, 2012). This study focuses mainly on the first type of talents, i.e. those of senior leaders, to assess their education-mediated talents and intelligence and study their moderating effects on the role and function of AI focus in firm performance.

2.2 AI and firm performance in different literature streams

The relationship between AI and firm performance has been examined in several different

streams of literature (see *Appendix 1*).

Firstly, the ***information management stream*** focuses on the technological drivers of the implementation of AI, aiming to understand how Big Data analytics capability (BDAC) improves different components of firm performance, and critical mediators have also received considerable attention. Two fundamental approaches, DCT and organisational learning theory (OLT), appear within this stream as a theoretical basis for studying AI focus and firm performance. First, DCT emphasises the importance of different types of complementary resources that organisations should cultivate to realise business value from AI investment. Rialti *et al.* (2019) empirically confirmed BDAC–ambidexterity/agility–firm performance relationships. Integrating DCT and adopting a source-position performance framework, Xie *et al.* (2022) also identified a positive relationship between BDAC, market responsiveness agility and operational adjustment agility via strategic agility, improving firms’ financial, market and operational performance. However, operational adjustment agility does not significantly mediate the link between BDAC and firm performance.

The second approach, OLT, provides a basis that focuses on the perception of environmental changes that influence the perceived information and learning process to obtain new knowledge when the information is contextualised and actioned. Based on this review, Zhu, Dong and Luo (2021) suggest firms should consider the levels of complexity, dynamism and munificence in the industry environment, as this might influence BDAC-firm performance in both operational efficiency and business growth. As a result, ambidexterity and agility emerge as essential mediators in the relationship between BDAC and financial, market and operational performance, and the industry environment is a critical moderator in this relationship, also reflecting the importance of information processing and learning in AI–firm performance relationships. This area primarily focuses on the cognitive response from the industry environment, including a lack of understanding of how consumers process information from AI technologies.

The ***service marketing stream*** focuses on how AI can improve employee performance, work engagement and the servicescape when consumers interact with AI-related services, as well as the key factors influencing Big Data analytics and AI capabilities that improve firm performance. Similarly to its use in the information management literature, DCT explains the relationship between AI, employment performance and financial performance and also asserts that AI-related services can lead to a dramatic and foundational firm transformation to

demand-dynamic economics focused on customers, partners and the public, firm performance and variability management. Davis *et al.*'s (2012) study confirmed this hypothesis by investigating smart manufacturing, manufacturing intelligence and demand-dynamic performance relationships.

On the other hand, to understand business performance and AI methods in the form of machine learning and deep learning, Ahmed *et al.* (2021) identified several ways that machine learning affected business performance, including information gathered from customers, better customer service, monitoring systems and quality control. As a result, this shows that various AI methods applied to services can perform multiple tasks, constituting a key source of employment performance and financial performance. This also reflects the importance of service factors in AI–firm performance relationships. However, this domain still primarily focuses on the impact of AI on financial and operational performance in B2B settings, while understanding the role of AI in customer responses remains unexplored.

Regarding the *innovation management stream*, unlike service marketing, which focuses on service design and the servicescape, innovation management emphasises the role of AI in the way firms operate and innovate, with far-reaching consequences for markets, economies and societies (Agrawal, Gans and Goldfarb, 2019). Rammer *et al.* (2022) provide an empirical analysis linking AI to new activities in business creation, considering various AI approaches and application domains. Moreover, the innovation impact of AI chiefly refers to three areas of enterprise: products, services and business models; production, delivery and management processes; and R&D and innovation processes. This study adopts an integrated view of different theoretical perspectives, such as DCT and contingency theory, which contribute to understanding the effects of BDAC and artificial intelligence capability on firm performance by using environmental dynamism as a moderator (Naz, Haq and Nasir, 2022).

Two critical theoretical approaches that appear with relative frequency are RBV theory and disruptive innovation theory. Based on the RBV perspective, firms can achieve a sustainable competitive advantage based on the organisation of their resources and use sense-making to efficiently respond to changing market conditions, including their assets, capabilities, knowledge, relationships and organisational process (Barney 1991). In terms of the role of AI in the innovation management domain, this perspective has been used to focus on sharing and combining local and foreign resources and capabilities to help with export decisions, as well as using innovation capability to ultimately improve export performance (Mikalef and Gupta

2021; Wamba-Taguimdje *et al.*, 2020).

Empirical studies (Yang, Ying and Gao, 2020; Cappa *et al.* 2021) that apply RBV theory find that implementing AI (volume, variety and accuracy) positively affects financial performance and innovation performance. Some studies have verified the intermediary role of dual innovation to study the impact of BDAC on organisational performance, concluding that dual innovation has a positive moderating effect on the impact of BDAC and organisational performance (Su *et al.* 2022). As a result, strategic resources and capabilities, such as innovation ambidexterity, can bring an advantage to the firm that results in superior performance. This reflects the importance of product development and organisational innovation processes' resources and capabilities in AI–firm performance relationships. Given the critical role of AI in innovation management, research in this area is rapidly emerging, including the study of the drivers, dynamics and potential performance outcomes of AI.

Finally, the *IT management stream* has become widespread in relation to professional activities, resulting in major organisational transformation and impacting all core processes and operations. Many businesses use traditional or sophisticated IT technologies to achieve strategic marketing objectives (Ruhle, Braun and Ostermann, 2008). In the field of knowledge of IT management, the critical theoretical basis is competitive strategy theory. From this perspective, IT is vital in the relationship between strategy and financial performance (Wooldridge and Floyd, 1990). DCT and the RBV approach are also used in this knowledge field to explain how the industry as a moderator influences the link between IT capability and business performance; an empirical study by Chae *et al.* (2018) concluded that different levels of industries where the strategic role of “transformation” IT was dominant outperformed IT leaders (Chae *et al.*, 2018). By integrating the RBV and DCT approaches, it can be seen that Big Data and predictive analytics determine the positive impact of IT deployment and human resources capabilities on organisational performance (Ma, Zhang and Yin, 2021; Mishra *et al.*, 2018; Wang, 2022).

Another approach applied in this knowledge field is machine learning theory, which can be shallow or deep. It is a subset of AI that automatically learns from collected data and makes predictions and/or decisions. It also identifies decision-making rules using statistical induction methods without the need for human-prescribed rules. Firms can learn from data and make predictions and/or decisions without human-specified rules, usually in market analysis, customer analysis and neural networks. An empirical study by Lee, Kwon and Pati

(2019) focuses on the role of IT in the interaction between the acquirer and target firm in a successful acquisition process through a machine learning theoretical perspective. It shows that IT distance is negatively related to the acquirer's post-acquisition performance. As a result, the various AI methods and systems adopted are crucial to firm performance. *Table 2.2* summarises some of the most widely applied theories.

Table 2.2 Theories used in the existing AI and firm performance literature

Theory	Definition	Scope	Limitations	Exemplars
RBV	Firms can achieve a sustainable competitive advantage by organising their resources and using sense-making to respond efficiently to changing market conditions.	The focus is on sharing and combining local and foreign resources and capabilities to help with export decisions and using innovation capabilities to improve export performance.	RBV is static in nature and is limited in its ability to address dynamic issues such as timing, innovation and entrepreneurship.	Wu <i>et al.</i> (2022) Cappa <i>et al.</i> (2021) Keshavarz <i>et al.</i> (2021) Mikalef and Gupta (2021) Su <i>et al.</i> (2022)
Dynamic capabilities theory	Dynamic capabilities refer to a corporation's ability to reconfigure, integrate and coordinate internal and external skills to deal with turbulence in commercial scenarios.	The focus is on the different types of complementary resources that organisations should cultivate in order to be able to realise business value from their AI investments.	Dynamic capabilities extend RBV, and firms update and reshape their business models and strategies to respond favourably to external environments.	Chatterjee <i>et al.</i> (2022) Wamba and Queiroz (2022) Wang, Lin and Shao (2022) Wijayati <i>et al.</i> (2022) Behl <i>et al.</i> (2022)

TOE	The TOE framework is characterised by three key aspects: technical, organisational and environmental. Technology is the domain of design and implementation, where the technology being designed and used is defined. Organisation refers to determining what is intended to be achieved with the design. The environment that is created is the domain that was desired to be accomplished.	The focus is an effective communication framework for evaluating new ideas and ideas that are shown to be useful to others.	The TOE framework inspires creativity and is a vital tool for defining the purpose of a project. Clearly articulating the aims and objectives of the project allows a whole project to be staffed with a team of people who understand the context in which the project will take place, the skills needed and the knowledge required to complete the project.	Chowdhury <i>et al.</i> (2022b) Mustapha (2022) Nasrollahi, Ramezani and Sadraei (2021) Yadegaridehkordi <i>et al.</i> (2020)
Machine learning theory	Machine learning can be shallow or deep. It is a subset of AI that automatically learns from collected data and makes predictions and/or decisions. It identifies decision rules using statistical induction methods without requiring human-prescribed rules.	The focus is on “learning from data and making predictions and/or decisions” without human-specified rules, usually in market analysis, customer analysis and neural networks.	Machine learning needs to rely on a large amount of data in the company, so the database's perfection, source and quality determine the machine learning results.	Lei <i>et al.</i> (2022) Yu, Khan and Umar (2022) Lee, Kwon and Pati (2019)
Knowledge-based view (KBV)	Knowledge is viewed as the most important organisational resource. Organisations are responsible for collecting, updating, and implementing knowledge into their marketing activities.	The focus is on adapting to and learning from the marketplace. Firms need the stamina to support exporting activities continuously through knowledge gained from host	Knowledge creation is a complex and expensive task for businesses, so it may be more cost-effective to imitate competitors in a corporate setting.	Chowdhury <i>et al.</i> (2022a)

		markets.		
Contingency theory	Contingency theory holds that there is no best way to adopt and implement AI; rather, different contingencies in the internal and external environment must be considered.	The focus is on the organisational adoption and use of AI.	Contingency theory originates in organisational theory, which is based on two core findings: first, there is no single best way to organise or manage a company, and second, every specific method a company may choose to organise or manage is not equally effective.	Vitari and Raguseo (2020) Raut <i>et al.</i> (2018)
Networks Theory	A network is built on relational data and can be defined as a set of actors (such as individuals or groups) with some pattern of relationships or interactions between them.	The focus is on AI platform value, such as social media platforms.	N/A	Wang, Lin and Shao (2022) Zhang (2022)
Organisational learning theory	Organisational learning theory utilises the dynamic interaction between the learning that occurs in AI algorithms and the learning that occurs in the organisation.	The focus is on organisational learning through AI projects.	N/A	Zhu, Dong and Luo (2021)

Economic Theory/Management Economics	In business management, the economic theory is an umbrella framework related to all the models impacting firm efficiency and performance. In a narrow sense, it often refers to managerial economics, which aims to generate rational and reasonable strategies. Managerial economics concerns more on rational decisions to maximise the profits of a firm, such as cost control and lean management.	In business management, economic theory facilitates firms to take reasonable and transparent strategies by firms, aiming at generating reasonable ideas and decisions which are assumed to produce significant change in management norms.	Economic theory, such as managerial economics, cost control, and lean management, tries to maximise a firm's financial benefits. However, it is criticised for failing to fulfil the firm's social and ethical obligations before profits.	Douglas & Callan (1992) Fahyan (2011) Gilboa <i>et al.</i> (2022) Org (1998)
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2.3 Artificial intelligence focus background

2.3.1 Artificial intelligence

AI is a branch of computer science concerned with making computers exhibit certain forms of intelligence and perform tasks better than humans (Shukla and Jaiswal, 2013). AI systems think and act like humans (Chukwudi *et al.*, 2018). AI can perform activities and react similarly to humans (Wamba-Taguimdje *et al.*, 2020). AI systems have human-like complex capabilities of reasoning, learning, decision-making and self-correction (Lou *et al.*, 2022; Shrestha, Krishna and von Krogh, 2021, 2021; Sze *et al.*, 2017; Mata *et al.*, 2018). These capabilities include not only the capacity for knowledge and the ability to learn new concepts and tasks but also the ability to judge, understand relationships and produce original thoughts (Mata *et al.*, 2018). AI refers to using machines to simulate human intelligence processes (Hasija and Esper, 2022; Kersting, 2018; Wamba-Taguimdje *et al.*, 2020).

In addition, as seen in the definitions (*Table 2.3.1*) of AI in the literature, some scholars focus on AI that does not require explicit programming to perform intelligent tasks (Demlehner and Laumer, 2020). It should be able to perceive, interpret, learn, plan, understand and take its own actions (Demlehner and Laumer, 2020; Kolbjørnsrud, Amico and Tomas, 2017; Wang, Huang and Zhang, 2019), which means that AI should be able to correctly interpret external data, learn from this data and use this learning to achieve specific goals and tasks through flexible adaptation (Makarius *et al.*, 2020). Therefore, there are two main ways to define AI. The first of these is to describe AI as a problem-solving tool to solve specific tasks that may or may not be time-consuming for humans (Demlehner and Laumer, 2020; Macarius *et al.*, 2020). A second definition sees AI as a system of cognitive processes that mimic human intelligence, such as the ability to interpret, reason and learn (Mikalef and Gupta, 2021). There are some similarities between the two definitions, but there are also some crucial differences. The similarity is that a common concept in both

categories is that AI will not necessarily replace humans but rather will act as an augmented agent to perform complex and time-consuming tasks (Mikalef and Gupta, 2021). However, in terms of their differences, one class of definitions assumes that AI is fully capable of imitating human behaviour (Kolbjørnsrud, Amico and Tomas, 2017; Wang, Huang and Zhang, 2019), and the other class of definitions treats AI as a tool, assuming it cannot fully replicate human capabilities (Wamba-Taguimdje *et al.* 2020). Secondly, some definitions refer to AI as a discipline of scientific inquiry (Schmidt *et al.*, 2020), while others see the concept as an applied-ability system or machine (Afiouni, 2019; Lee, Kwon and Pati, 2019). For the purposes of this study on firm performance, the position is taken that AI is an applied discipline designed to enable systems to recognise, interpret, infer and learn from data to achieve predetermined corporate and social goals.

Table 2.3.1 The definitions of artificial intelligence

Author(s) and date	Definition
Kolbjørnsrud <i>et al.</i> (2017)	AI is defined as computers and applications that sense, comprehend, act and learn.
Lee <i>et al.</i> (2019)	AI is defined as an intelligent system created by using data, analysis and observation to perform certain operations, but it can complete tasks in a timely manner without programming.
Makarius <i>et al.</i> (2020)	AI is defined as the ability of a system to correctly interpret external data, learn from these data and use these learnings to achieve specific goals and tasks through flexible adaptation.
Mikalef and Gupta (2021)	AI is defined as the ability of a system identification to recognise, interpret, infer and learn from data to achieve predetermined organisational and social goals.
Ahmed <i>et al.</i> (2022)	AI approaches will be in the form of machine learning, deep learning and digital technologies.
Wang <i>et al.</i> (2022)	AI is defined as tools, products, and systems that make accurate decisions in the shortest possible time, including applications and analytics based on operational and analytical databases.

2.3.2 AI technology

Hasija and Esper (2022) defined AI when studying how organisations and managers benefited from using AI in operations by investing in AI technology acceptance. The study identified the various forms of AI technologies to highlight the benefits of AI technologies in supporting the operational effectiveness of organisations. AI is defined as the simulation of human intelligence processes with the supportive roles of machines, such as computer systems, in supporting the decision-making of managers and organisations. AI technologies are the specific applications of AI, such as natural language processing (NLP), expert systems and machine vision. AI technology can be designed into different intelligent programs, just as humans are used for other tasks (Huang and Rust, 2020). According to Huang *et al.* (2019), AI can be divided into three types: mechanical AI, thinking AI and feeling AI. These three types also demonstrate an evolution of AI technology from low intelligence to high intelligence.

Mechanical AI is designed to automate repetitive and routine tasks and offers the benefits of standardisation, for example, by using collaborative robots to help with packaging, drones to deliver goods and self-service robots to provide services (Mende *et al.*, 2019; Huang and Rust, 2020). Thinking AI is a new conclusion-reaching or decision-making form designed to process data. It provides personalisation benefits (e.g., text mining, speech recognition, face recognition and machine learning). The most common applications in marketing are various personalised recommendation systems (Chung, Wedel and Rust, 2016), such as Netflix movie recommendations and Amazon cross-selling recommendations. Feeling AI is designed for two-way interaction to analyse human feelings and emotions and provides the benefits of relationalisation (Huang and Rust, 2020). Some current technologies include emotion analysis, NLP, text-to-speech technology and recurrent neural networks (McDuff and Czerwinski 2018). A wide range of marketing functions involve feelings, such as customer satisfaction, customer complaints, customer sentiment, sentiment in advertising, etc.

The major types of AI literature where technologies are defined highlight some critical aspects of the definitions and outline some crucial differences in terms of their areas of application. These essential AI techniques have been tested in empirical studies and are listed in *Table 2.3.2*. Today, most of these techniques are combined with machine learning or deep learning to provide solutions that can evolve and learn, such as NLP and machine learning applications in the case of chatbots (Baby, Khan and Swathi, 2017). The features enable chatbots to understand and communicate using human language through NLP. On the other hand, machine learning algorithms help chatbots learn and evolve as they have access to more data (Castillo, Canhoto and Said, 2021). Notable types of AI technology research in other information system (IS) empirical studies are also listed in this table.

Table 2.3.2 Definition of main AI technologies

Technology	Definition	Reference(s)
Machine learning	-Machine learning is the subset of AI capable of “learning from data and making predictions and/or decisions” without human-dictated rules. -Machine learning uses an inductive approach in which statistical methods identify decision rules based on collected data.	Afiouni (2019) Schmidt <i>et al.</i> (2020)
Deep learning	Deep learning can derive structure from data in a multi-layered manner. What differentiates deep learning from more traditional machine learning is the use of artificial neural network architecture.	Wang <i>et al.</i> (2019) Afiouni (2019) Wamba-Taguimdje <i>et al.</i> (2020)
Natural language processing	NLP is the process through which machines can understand and analyse language as used by humans.	Jarrahi (2018)
Computer vision	Computer vision refers to the algorithmic inspection and analysis of images.	Jarrahi (2018)
Expert system	Expert systems aim to imitate human decision-making by capturing and representing the expertise of experts for other organisational members to use, serving as a knowledge base.	Afiouni (2019); Lichtenthaler (2019)

Planning and scheduling	The development of action strategies and sequences for subsequent execution.	Lichtenthaler (2019)
Speech synthesis systems	-Includes text-to-speech and speech-to-text solutions. Text-to-speech is the production of speech by machines through the automatic conversion of text into a phonemic specification of pronunciation of the sentences to be uttered. Speech-to-text systems take a human speech utterance as an input and require a string of words as output.	Lichtenthaler (2019) Damper <i>et al.</i> (1999) Ghadage and Shelke (2016)

2.3.3 AI capability

The definition of AI capability suggests that the concept is developed from the definition of AI technologies as the extent to which firms have specific capabilities to use AI technologies (Salib *et al.*, 2021). As AI becomes an increasingly important asset for organisations, there is a growing body of research on how to harness these technologies and techniques to achieve organisational goals (Bytniewski *et al.*, 2020; Schmidt *et al.*, 2020; Wang, Huang and Zhang, 2019). Therefore, it is imperative to introduce the concept of AI capabilities to explain how to achieve this value and how enterprises should organise investment in AI. For example, Wang (2022) studied the benefits of AI capability by referring to AI-enabled IT capability as an example to study how AI capability contributed to organisational performance. The findings suggested that AI capability contributed to budget management and improved organisational performance with the rapid development of IT, which is an important supportive form of technology to enhance the AI capability of corporations. From others, such as Umar *et al.* (2022), an integrated industry emerges as a variety of digital technologies and tools are used for organisations to better connect with different stakeholders. Under the influence of the Fourth Industrial Revolution (4IR), organisations will undergo changes in the entire business process, including product design, operations and product delivery (Song *et al.*, 2023).

Ten capacities are listed to evaluate organisations' AI development capabilities in

implementing AI technologies. The specific capabilities can be explained using the definitions shown in *Table 2.3.3*. These definitions are not the same, but they all contain a basic concept. AI development capabilities refer to how an organisation harnesses its specific AI-enabled resources to create value (Schmidt *et al.*, 2020; Wamba-Taguimdje *et al.*, 2020). These AI enablement-specific resources can be both technical, such as training data and AI algorithms (Schmidt *et al.*, 2020) and non-technical, such as employee skills (Wamba-Taguimdje *et al.*, 2020). Therefore, the concept of AI development capabilities expands the perspective of AI capabilities to not only focus on the technical resources of AI but also to include all other relevant necessary organisational resources that are still empowered by AI technology to realise the strategic potential of AI fully.

Table 2.3.3: Sample definitions of capabilities in various technologies

Name of Capability	Author(s) and date	Definition
AI capability	Thummadi (2021) Mikalef and Gupta (2021)	AI capability is defined as a firm's ability to select, orchestrate, and leverage its AI-specific resources.
4IR technological capabilities	Hofmann and Rüsch (2017) Umar <i>et al.</i> (2022) Yu, Khan and Umar (2022)	4IR technological capabilities are defined as integrated industry or intelligent manufacturing, involving the ability to affect the entire business of product design, manufacturing, and final product delivery.
Big Data Analytics capabilities (BDACs)	Mikalef <i>et al.</i> (2019) Su <i>et al.</i> (2022) Xie <i>et al.</i> (2022) Olabode <i>et al.</i> (2022) Chun (2018)	The concept of BDACs can be defined as the ability to dynamically and effectively arrange and deploy data, data management, and data technology, as well as the talent to generate new insights to make decisions in real time.
Knowledge-based dynamic capabilities view	Tortora <i>et al.</i> (2021) Gonzalez (2022)	Knowledge-based dynamic capabilities are defined as requiring dynamic capabilities, being able to modify operational capabilities, using predefined routines to convert inputs into outputs, and supporting the organisation's current operations to ensure competitiveness in a rapidly changing environment.
IT capability	Chae, Koh and Park (2018) Erkmen, Günsel and Altındağ (2020) Wang (2022) Wamba-Taguimdje <i>et al.</i> (2020)	IT capability is defined as a unique resource, and an enterprise can also comprehensively use resources and promote the efficient allocation and use of various resources inside and outside the organisation.
Enterprise resource planning capability	Uwizemungu & Raymond (2012) Raoof <i>et al.</i> (2021)	ERP capabilities are a subset of IT capabilities that make ERP systems particularly easy to use.

Supply chain capabilities	Wu <i>et al.</i> (2006)	Supply chain capabilities involve a firm's ability to assimilate, utilise, and identify external and internal information/resources to facilitate supply chain activities across the organisation.
Dynamic capabilities	Teece, Pisano and Shuen (1997)	Dynamic capabilities refer to firms' ability to integrate, build, and reconfigure internal and external competencies to address the changing business environment.
Network capabilities	Argyaki and Cheriton (2005)	Network capabilities are defined as the more information a platform learns from collected user data, the greater the platform's value to each user, and the platform will exhibit data network capabilities.
Digital platform capabilities	Jun <i>et al.</i> (2021)	Digital platform capabilities refer to the capacity of organisations to combine people, processes and tools.
Organisational capability	Hase (2000)	Organisational capability is how an organisation brings together its people and other resources to respond to changes in the business environment and offer value to customers and stakeholders.

2.3.4 AI adoption and use

As well as recognising the role of AI technologies and their importance in developing AI capabilities, scholars have also focused on AI adoption, which is defined as adopting AI technologies to improve the AI capabilities of corporations (Smit, Eybers and Smith, 2022; Kabalisa and Altmann, 2021). The IBM Global AI Adoption Index defines AI adoption as the ratio of businesses that adopt AI technologies to support their operations (Smit, Eybers and Smith, 2022). For example, 35% of firms report adopting AI technologies in their operations, which means the AI adoption ratio is 35%. Kabalisa and Altmann (2021) defined AI adoption within organisations, especially transnational corporations, in order to study the departments or business units that adopted AI technologies in their operations. From the firm-level definition, the AI adoption ratio suggested that corporate departments or business units adopted AI technologies to support their daily operations.

There are opportunities to study the benefits of AI adoption that corporations can

apply to support their competitive advantage. Wang *et al.* (2021a) suggested that promoting AI adoption could promote employee engagement and contribute to the improved performance of individual employees in management practices. Bhatt (2022) examined the value of AI technologies in the hiring process, indicating that AI adoption could enhance efficiency in recruiting and selecting corporate candidates. Schmitt (2019) identified the barriers to achieving AI adoption in corporations by examining the potential resistance of employees who are not used to AI technologies compared with those who are used to traditional ways of work. Other researchers found that enablers and barriers to AI adoption could be broken down into three broad categories according to the TOE framework: technology, organisation and environment (Tornatzky, Fleischer and Chakrabarti, 1990). Technology is the domain of design and implementation, in which the design and type of technology being used are defined. Organisation relates to what is intended to be achieved with the design. The environment created is the domain of what was intended to be accomplished (Baker, 2012).

AI use is defined as the specific applications of AI technologies. AI has a wide range of applications across various industries and fields, such as in marketing, production management, enterprise management and customer service (Alsheiabni *et al.*, 2018; Jelonek *et al.*, 2020; Wamba-Taguimdje *et al.*, 2020). There are various ways to use AI technologies, which benefit operations for different types of businesses and concern different business functions. Depending on their purpose, AI applications are broadly divided into two categories: AI for automation and AI for augmentation. Automation refers to AI systems that replace human jobs, while augmentation technologies augment human intelligence by providing insights that aid decision-making.

Automation is an established concept related to the replacement of humans by machines. However, advances in AI have enabled machines to learn, improve and adapt, thereby enhancing performance and automating more complex tasks (Lee,

Kwon and Pati, 2019; Coombs *et al.*, 2020). This automation involves higher-level cognition and decision-making rather than just mechanical, repetitive tasks, which is the concept of intelligent automation (Welling, 2019). Augmentation refers to the use of AI to enhance human capabilities and improve performance rather than simply replacing human workers with machines. This approach combines human intelligence and skills with AI-powered technologies to achieve better outcomes, greater efficiency and increased productivity (Schmidt *et al.*, 2020).

2.3.5 AI focus

AI's focus is related to specific areas, and AI technology is applied to support business operations and achieve development and improvements in efficiency and cooperative development, such as healthcare areas that apply AI to achieve development and continuous improvements (Fukuzumi *et al.*, 2019). In addition, from the perspective of service providers, the organisation uses or adopts AI to develop specific business units or fields in order to achieve the advancement of the service industry (Albrecht, Rausch and Derra, 2021; Mishra, Ewing and Cooper, 2022). Based on the literature review, it is justifiable that AI focus can be considered as referring to focusing on specific domains that use cutting-edge technologies enabled by AI to support business operations and to realise cooperative development and efficiency improvement between employees and organisations (Albrecht, Rausch and Derra, 2021; Fukuzumi *et al.*, 2019; Chukwudi *et al.*, 2018; Wamba-Taguimdje *et al.*, 2020; Mishra, Ewing and Cooper, 2022). AI focus can also relate to the implementation or forthcoming application of specific aspects of AI technology at the company level. According to the best definition of AI in the previous literature, it is a set of technologies aimed at using machines to approximate certain aspects of human or animal cognition (Calo, 2017; Zhuo, Larbi and Addo, 2021).

According to Huang and Rust (2018) and Syam and Sharma (2018), AI is demonstrated by machines that showcase various aspects of human intelligence and

mimic human intelligence behaviour. It relies on multiple vital technologies, such as machine learning, deep learning, NLP, rule-based expert systems, neural networks and robot process automation (Zhuo, Larbi and Addo, 2021; Davenport and Ronanki, 2018). Companies' application of AI in the market will be the main scope of our research. According to Huang *et al.* (2019), artificial intelligence can be divided into three types: mechanical AI, thinking AI and feeling AI (Huang & Rust, 2018; Huang *et al.*, 2019). However, these three types of intelligence have also completed the evolution of AI technology from low intelligence to high intelligence.

Mechanical AI is designed to automate repetitive and routine tasks; it offers the benefits of standardisation. For example, collaborative robots can help with packaging (Huang & Rust, 2020). Thinking AI is a new conclusion or decision designed to process data. It provides personalisation benefits (e.g., text mining, speech recognition, face recognition and machine learning). The most common applications in marketing are various personalised recommendation systems (Chung *et al.*, 2016; Huang & Rust, 2020), such as Netflix movie recommendations and Amazon cross-selling recommendations. Feeling AI is designed for two-way interaction to analyse human feelings and emotions; it provides the benefits of relationalisation (e.g., emotion analysis, natural language processing (NLP), text-to-speech technology and recurrent neural networks (RNN)). A wide range of marketing functions involve feelings (Huang & Rust, 2020), such as customer satisfaction, customer complaints, customer sentiment, and sentiment in advertising.

Figure 2 provides an overview of AI's historical perspective, and *Table 2.3.5* provides critical studies related to AI concepts and AI technology in this paper.

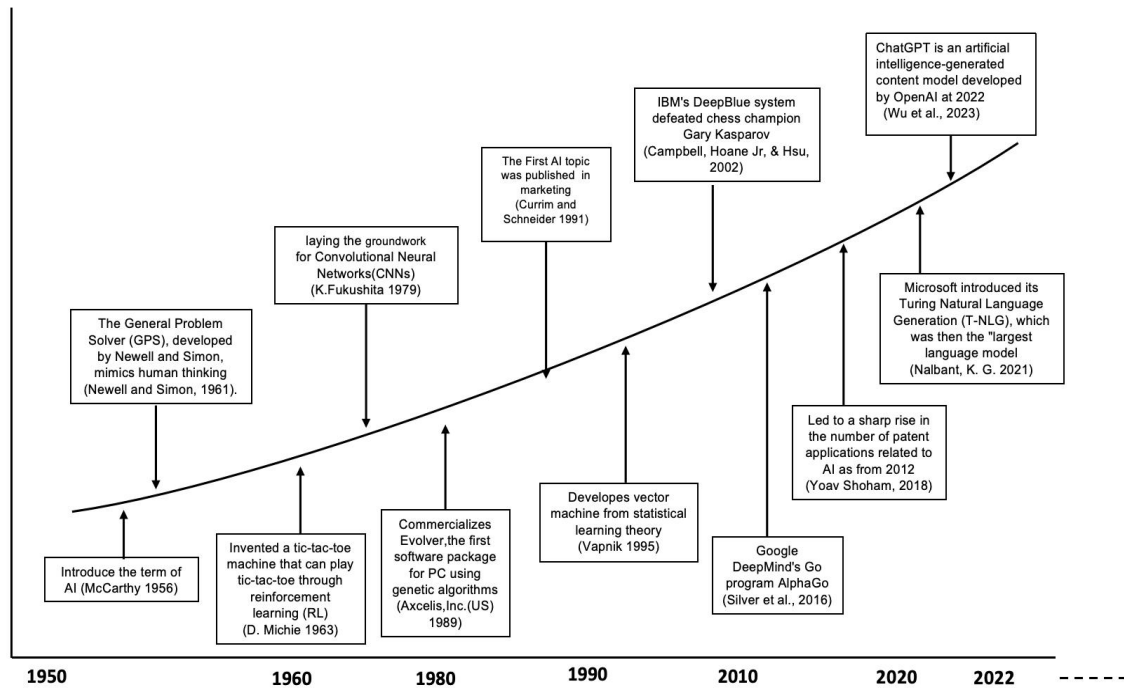


Figure 2. Temporal development and theoretical maturity of AI

Table 2.3.5 Key studies related to AI concepts

Publication	Definition (AI)	Aim/Objective	Key theories	Related AI technologies
Hasija and Esper (2022) <i>Journal of Business Logistics</i>	AI technology: AI is defined as the simulation of human intelligence processes with the supportive roles of machines, such as computer systems, in supporting the decision-making of managers and organisations. AI technologies are the specific applications of AI, such as natural language processing, expert systems and machine vision.	To explore factors related to customers' trust in AI and recommendations to improve AI technology acceptance.	Technology adoption; technology trust; thematic analysis of AI applications	AI-enabled software; AI-based technologies
Borra <i>et al.</i> (2022) <i>Applied Nanoscience</i>	AI technology: the new form of technology used by webs to gather Big Data, support data analyses and detect issues.	To study how Google's new AI technology changes the lives of human beings and how to improve people's acceptance of Google's new AI technology.	New product adoption cycle	Google's new AI technology, such as Google Maps and self-driving
Kinkel, Baumgartner and Cherubini (2022) <i>Technovation</i>	AI use: for manufacturing activities, applying AI technologies could also contribute to customised products and services.	To understand how AI could be used in manufacturing to improve customised products and services.	Customised manufacturing	Machine learning
Kinkel, Baumgartner and Cherubini (2022) <i>Technovation</i>	AI technology: technologies in manufacturing that collect data and conduct analyses on manufacturing companies.	To study requirements that managers should address concerning the adoption of AI technologies in manufacturing.	Prerequisites and enablers for the adoption of AI at the firm level	Machine learning, facial recognition systems, etc.
Smit, Eybers and Smith (2022)	AI adoption: IBM Global AI Adoption Index defines AI adoption as the ratio of businesses that adopt AI	To study the use of the IBM Global AI Adoption Index in	IBM Global AI Adoption Index; new	IBM Global AI Adoption Index

<i>Artificial Intelligence Research</i>	technologies to support their operations.	management.	technology adoption process	
Meyer-Waarden and Cloarec (2022) <i>Technovation</i>	AI use: AI use is defined as the specific applications of AI technologies, such as using AI in personalised shopping, AI-powered assistants, creating innovative content, personalised learning, voice assistants and autonomous vehicles.	To study how AI could be used in self-driving.	Technology adoption process	Big Data, self-driving vehicles
Bhatt (2022) <i>Foresight</i>	AI adoption: Improvements in AI adoption can always result in improved efficiency in recruiting and selecting corporations' candidates.	To study how AI is used in the hiring process.	Human resource management; hiring and selection process	AI recruiting tools
Wang (2022) <i>Systems Research and Behavioural Science</i>	AI capability.	To study how AI capability contributes to organisational performance.	Performance management	Spam filters for emails; algorithms
Mikalef <i>et al.</i> (2021) <i>Government Information Quarterly</i>	AI capability: AI capabilities contribute to the performance of government agencies.	To study how AI capabilities contribute to the performance of government agencies.	Urban planning and development, performance management, resource planning	Machine learning; autonomous vehicles

Surianarayanan and Chelliah (2021) <i>New Generation Computing</i>	AI capability: reflected as AI technologies that show excellent capabilities in auditing and responding to dynamics and challenges.	To study how corporations could harness AI capabilities to deal with COVID-19 containment.	Change management	Algorithms; Big Data; blockchain
Sjödin <i>et al.</i> (2021)	AI capability: AI capabilities promote business model innovation by supporting feedback loops.	To study how AI capabilities promote business model innovation.	Business model canvas	AI in e-commerce
Kabalisa and Altmann (2021) <i>Economics of Grids, Clouds, Systems, and Services</i>	AI adoption: from the firm-level definition, the AI adoption ratio suggests that departments or business units in corporations adopt AI technologies to support their daily operations.	To review the types of AI and motives for corporations to adopt AI to gain competitive advantages.	Motives for AI Adoption	A review of all types of AI: reactive, limited and self-aware
Thummadi (2021) <i>Responsible AI and Analytics for an Ethical and Inclusive Digitised Society</i>	AI capability: AI capability is the ability to select, use, and harness a firm's AI-related resources.	To study how AI can be successfully integrated into platforms; to explore the fundamental mechanisms that drive performance in digital platforms such as open source.	AI capabilities; open source software; performance management	Open source software
Salib <i>et al.</i> (2021)	AI capability: The concept is developed from the definition of AI technologies, which is the extent to which firms have specific capabilities to use AI technologies.	To study the extent to which firms have specific capabilities to use AI technologies.	Routine clinical workflow; operation management	AI used in hospitals; AI in health

Spence (2021)	AI technology: using the web and related data generated on the web to solve management issues.	To study the degree to which technology in the form of products and processes is capable of contributing to human enhancement and well-being.	A normative model based on rationalist and virtue ethics, as well as stoic philosophy	Types of AI: reactive, limited memory, self-aware
Wang <i>et al.</i> (2021a) <i>Information Systems Frontiers</i>	AI adoption: promoting AI adoption could promote employee engagement and improve individual employees' performance.	To study how promoting AI adoption can promote employee engagement and contribute to the improved performance of individual employees in management practices.	Employee engagement; performance management	AI in human resource management; Big Data; machine learning; AI-supported performance management systems
Lucero <i>et al.</i> (2020) <i>Engineering Psychology and Cognitive Ergonomics</i>	AI use: AI use includes occasions of designing and creating customised games.	To study how AI could be used in game management.	Real-time strategy games	Big Data, machine learning, AI in games
Schmitt (2019) <i>Marketing Letters</i>	AI adoption: defines the barriers to achieving AI adoption include resistance from the managers and the employees.	To study how to use AI and robots in marketing successfully.	Marketing	AI robots
Fukuzumi <i>et al.</i> (2019) <i>Information in Intelligent</i>	AI Focus: This focuses on understanding new guidelines about AI development by analysing the legal, social, and ethical issues organisations face when developing	To understand new guideline items about AI development.	Ethics, legal and social issues in analysing AI development-related issues	A general focus on all types of AI

<i>Systems</i>	specific business units or areas with AI from the perspective of service providers.			
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2.4 Firm performance outcomes from AI

2.4.1 Competitive advantage

Competitive advantage refers to the factors that give a company an edge over its competitors in the market. These factors can be a product or service feature, a company's reputation, technological advancements or any other factor that distinguishes it from its competitors (Malega *et al.*, 2019). The company's position is determined by how well its products and services compare with those of its competitors. Many components of the company's market, such as customer demand and current trends, are considered by a marketing team to make their position more competitive. By using AI, it is expected that firms will take into account all facets of the market when determining where the organisation and product will best fit and, hence, gain some competitiveness. Many businesses that have adopted the Internet of Things (IoT) have gained a competitive advantage through better products and services. As a result, they have been able to take advantage of more opportunities in the digital age. Furthermore, the IoT can be used to improve a company's relationship with its customers through information sharing (Jonny and Toshio, 2021).

When migrating to smart technologies to compete in the market, manufacturers need to improve their skills in a standardised, objective and reproducible way, as became apparent during the pandemic. Therefore, the challenge of digital transformation in the post-pandemic era is not only for businesses to rethink entrepreneurial activity but also to take action to redefine their skills. Abai, Yahaya and Deraman (2015) posit that the power of data has inspired the deployment of business intelligence and analytics in most enterprises. New digital technologies based on digital transformation are factors that influence a company's DCs and enable organisations to seek, explore, acquire, absorb and apply knowledge resources more effectively. This changes the competition scenario because it is considered an ability (Tortora *et al.*, 2021).

As proof of that, implementing the latest technology now has the potential to

restructure a company's operations faster and more efficiently. This is not possible without taking advantage of the possibilities of digital transformation. Big Data and AI can potentially disrupt established industries and regional monopolies. Data from management discussions and the analysis of word frequencies are used to test theoretical predictions about the intensity of digital transformation at the business level. Cavusgil, Knight and Riesenberger (2008) found a considerable influence on productivity from digital transformation in the workplace, which has the potential to threaten regional and national monopolies. According to other studies, digital transformation substantially impacts innovation both inside and outside companies, which in turn improves corporate performance and helps companies to outpace their competitors (Guo *et al.*, 2023).

2.4.2 Process efficiency

Process efficiency refers to the ability of a system or process to produce desired outcomes with minimal waste, effort and resources. Implementing AI technologies or software tools can improve process efficiency (Coombs *et al.*, 2020; Enholm *et al.*, 2022). Automating tasks through AI can allow organisations to offload some of their employees from repetitive, day-to-day tasks, which will enable them to focus on other knowledge-intensive activities that add more value to the organisation (Makarius *et al.*, 2020), thereby increasing their productivity (Duan, Edwards and Dwivedi, 2019; Naim, 2022; Balasundaram and Venkatagiri, 2020; Bytniewski *et al.*, 2020; Ahmed *et al.*, 2022; Lui *et al.*, 2022). In the financial field, managers are using AI models to improve revenue and minimise costs by improving and speeding up decision-making in the management process (Naim, 2022). By using AI-based tools like performance monitoring applications, managers in the field of personnel management (PM) want to raise employee productivity. Moreover, AI has the power to alter management decision-making processes (Duan, Edwards and Dwivedi, 2019).

AI can definitely reduce the time required to complete some key business processes

and improve the error rate (Ashfaq *et al.*, 2020; Pan *et al.*, 2022; Papagiannidis *et al.*, 2023; Holzinger *et al.*, 2023). AI technologies, such as machine learning, NLP and computer vision, can automate tasks previously performed manually, such as data entry, document processing and quality control. This can significantly reduce the time required to complete these tasks and minimise the risk of errors (Reddy *et al.*, 2019; Pan *et al.*, 2022; Papagiannidis *et al.*, 2023).

In addition, an AI-powered chatbot can handle real-time customer inquiries and support requests, reducing response time and improving customer satisfaction (Mnyakin, 2019; Ashfaq *et al.*, 2020). An AI-powered document processing system can extract critical information from large volumes of documents, such as invoices or medical records, faster and more accurately than a human. AI can also be used to improve the accuracy of decision-making processes by analysing large amounts of data and identifying patterns and trends that may not be apparent to humans (Holzinger *et al.*, 2023). This can be particularly useful in areas such as fraud detection, predictive maintenance and supply chain optimisation.

2.4.3 Insight generation

The implementation of AI systems in organisations offers the advantage of insight generation. AI benefits the development of strategic flexibility because of routine and innovative AI use (Van de Wetering, 2022). Operational ambidexterity is enhanced, which refers to an organisation's capacity to improve its operational business process. Organisations need to harness AI to enhance strategic flexibility (Van de Wetering, 2022). For decision-makers in organisations, it is essential to ensure that various scenarios and issues are considered. Organisational ambidexterity is improved by providing cost-effective service excellence, especially when adopting a robotic service system (Wirtz, 2019).

Organisational agility is when a company can quickly adapt to changed situations in the business environment (Rawat and Barnes, 2022). It is essential for organisations

to be agile and adjust their businesses effectively to respond to the changing business environment, which enhances business competitiveness (Kurniawana and Hamsalb, 2019). Organisational agility is essential, as strategic flexibility indicates that organisations can make efforts to innovate and seek better performance and effectiveness (Atkinson *et al.*, 2022). AI systems explore and develop knowledge from Big Data analytics, while effectiveness is enhanced in organisations to seek organisational resilience (Holbeche, 2018).

Customer agility relates to the capacity of organisations to make effective strategic adjustments to respond to the needs of customers (Wang, Lin, and Shao, 2022). Customers' needs, either current or potential, can be predicted with the adoption of AI systems. Understanding customers' needs is an essential step for organisations to identify actions that will help them improve customer relationships and seek market competitiveness. Wang, Lin, and Shao (2022) point out that when organisations adopt AI-enabled chatbot tools, they can explore customer needs based on the data collected.

2.4.4 Business process transformation

Business process transformation is re-engineering and improving an organisation's existing business processes to improve efficiency, effectiveness and agility. It involves an AI systematic approach to change how work is carried out within an organisation to meet the evolving needs of customers, markets and stakeholders (Mishra and Pani, 2021). AI can enable organisations to innovate and transform their business processes by automating repetitive tasks, analysing data to make better decisions and improving customer experience (Wamba-Taguimdje *et al.*, 2020). When an organisation undergoes business process transformation, it often results in changes to the roles, responsibilities and workflows of employees. As a result, the existing organisational structure may no longer be optimal or efficient.

AI is increasingly becoming a driver for re-engineering and redesigning existing

organisational structures (Wamba-Taguimdje *et al.*, 2020). For example, a business process transformation that involves implementing new technology may require a new organisational structure that accommodates the new roles and responsibilities associated with the technology. Organisations may need to create new positions focused on data analysis, machine learning and NLP. These positions require different skill sets and competencies from traditional roles, and organisations may need to restructure teams and departments to accommodate these new roles (Makarius *et al.*, 2020). AI can also impact how work is organised and managed (Makarius *et al.*, 2020). For example, AI can facilitate the creation of cross-functional teams better suited to collaborate and solve complex problems. These teams may be organised around specific business processes or projects rather than traditional departmental structures.

However, implementing AI into a business process transformation can be complex and require significant investment. Businesses must carefully evaluate the costs and benefits of AI, as well as consider potential ethical and legal implications. Additionally, the successful implementation of AI requires a skilled workforce and a robust data infrastructure.

2.4.5 Financial performance

Financial performance is related to revenue growth and profitability, defined as a company's sales growth, inventory position and inventory growth rate, net profit margin, operating margin and profitability (Huang *et al.*, 2022). In recent years, AI has been gradually embedded into key organisational activities, promoting the business growth of various departments (Eriksson, Bigi and Bonera, 2020). The application of AI has improved organisations' competitiveness by increasing their productivity by reducing costs, productivity gains and boosting the quality of products and services given to customers (Obitade, 2022).

Organisations implementing AI solutions have achieved improved financial and accounting performance, such as increasing revenue and reducing costs (Alshahrani & Salam 2023; Davenport and Ronanki, 2018). As a result, AI has been shown in some studies to boost financial performance by providing fresh insights, assisting decision-making processes and increasing the productivity of corporate operations through better planning, production and quality management. However, so far, few studies have described other measures of financial performance in detail, such as return on investment, profitability and gross profit margin, after the introduction of AI (Enholm *et al.*, 2022). This means the impact of AI focus on firm performance is not fully understood and may have negative as well as positive consequences when other relevant factors and measures are taken into consideration.

2.4.6 Operational performance

In companies using AI technology, there may be better opportunities for business processes to have enhanced operational efficiency and product and service growth compared with their competitors (Mishra, Ewing and Cooper, 2022; Luo, 2022; Wamba-Taguimdje *et al.*, 2020). Operational performance can be said to be the sum of all the achievements of enterprises (Dubey *et al.*, 2021). AI can impact operational performance in several ways, for example, by introducing new products and services and enhancing the quality of existing ones (Davenport and Ronanki, 2018; Wamba-Taguimdje *et al.*, 2020). Management scholars believe that by using rich and up-to-date information to inform operational decisions and by rapidly developing better solutions, organisations can avoid costly courses of action such as overtime production, lost sales, excess inventories, etc. (Srinivasan and Swink, 2018; Dubey *et al.*, 2021). AI enables supply chain managers to reduce working capital, maximise returns on capital employed, increase inventory returns, improve product quality and improve product delivery (Bayraktar *et al.*, 2009; Srinivasan and Swink, 2018).

2.4.7 Innovation performance

Innovation is the process of manufacturing, management, business activities, R&D, and technical design, which involves improving product marketing (Alegre and Chiva, 2008). Innovation is defined as the use of new information resources and technologies to create, accept and implement new ideas (Calantone, Cavusgil and Zhao, 2002). Innovation performance can be broken down into innovation efficacy and innovation efficiency. Innovation efficacy refers to the degree to which innovation is beneficial to the enterprise. In contrast, innovation efficiency reflects the time and effort required to innovate in order to achieve the desired rate of return in relation to the degree of innovation (Alegre and Chiva, 2008).

AI can change the innovation landscape by analysing the fit between consumer preferences and increasing product features (Ghasemaghaei and Calic, 2020). Utilising AI methods allows companies to demonstrate efficient and effective corporate innovation, and several recent studies have found a positive correlation between AI and innovation success (Calantone, Cavusgil and Zhao, 2002; Yalcinkaya, Calantone and Griffith, 2007; Gunasekaran *et al.*, 2017; Johnson and Kalkbrenner, 2017; Ghasemaghaei and Calic, 2020). However, AI technology may not directly bring about better innovation performance (Johnson and Kalkbrenner, 2017; Ghasemaghaei *et al.*, 2018); in fact, the impact of AI on innovation performance can be adjusted by many mediating variables (Ghasemaghaei and Calic, 2020).

2.4.8 Market performance

Market performance refers to improving the position of enterprises in the market to gain competitive advantage (Maroufkhani, Wan Ismail and Ghobakhloo, 2020). A typical way that AI can improve marketing performance is to segment customers according to their needs and then aim at the market segments with different customised marketing strategies. AI can strengthen customer segmentation by processing and learning from existing customer data so that enterprises can

understand customer preferences and lifestyles in a new way (Enholm *et al.*, 2022). This function can achieve more precise segmentation because organisations can classify customers more finely (Mishra and Pani, 2020). Therefore, organisations can better position their marketing objectives and provide the possibility of one-to-one marketing through personalised experience (Mishra and Pani, 2021). Thus, AI improves marketing efficiency and accuracy by using the right marketing strategy to target the right customers. In addition, with the change in customer behaviour, the segmentation suggestions in the AI system will be regenerated so the organisation can effectively adjust its marketing strategy (Enholm *et al.*, 2021). However, little focus has been paid to whether AI may also negatively affect market performance since it necessitates other changes to the organisation that may prove detrimental, as well as raise costs, as discussed above.

2.4.9 Employee performance

Employee performance can be referred to as job performance, which is defined as the employee's performance in the job being equivalent to delivering the results expected by the organisation with regard to the quality of work, quantity of work, and hours worked (Wijayati *et al.*, 2022). According to Peterson and Plowman (1953), the quality of work involves procurement, production, quality inspection and delivering goods and services that meet set standards. Quantities of work are units of output produced by employees' actions, such as product volumes, waste volumes and sales figures (Peterson and Plowman, 1953).

AI significantly impacts employee performance and job engagement (Wijayati *et al.*, 2022) because it can help employees work more efficiently and effectively by automating repetitive tasks and providing them with data-driven insights and recommendations. This can free up employees to focus on more strategic or creative tasks, leading to increased productivity and job satisfaction (Wijayati *et al.*, 2022). Additionally, AI can provide employees with personalised training and development

opportunities, helping them continuously improve their skills and stay up-to-date with the latest industry trends (Bandari, 2019).

2.4.10 Sustainability performance

With the rapid increase in people's awareness of the importance of sustainable development, the performance impact of AI on a company's sustainable development will also follow. AI can potentially impact individuals and societies in disruptive ways over the long term (Sahoo *et al.*, 2022). AI's corporate sustainability performance evaluation will focus on the two dimensions of environmental and social issues. From an environmental perspective, AI can impact environmental sustainability, for example, by minimising energy costs and reducing energy consumption, thus reducing negative environmental impacts (Borges *et al.*, 2021; Sahoo *et al.*, 2022). Alternatively, the AI tools used can also help organisations reduce pollution and waste (Toniolo *et al.*, 2020). A growing body of research is examining the role of AI applications in supporting circular economy strategies by enabling organisations to implement strategies that promote recycling, reducing emissions and reusing materials (Rajput and Singh, 2019; Pinheiro, Oliveira and Lozano, 2022). This results in an eco-friendly reputation and various competitive advantages, resulting in increased cost efficiency and profitability (Sahoo *et al.*, 2022).

From a social perspective, by considering social responsibility, organisations can improve their reputation and increase their market share, which in turn affects their competitive advantage (Toniolo *et al.*, 2020). However, social responsibility also brings many new challenges regarding privacy protection and discrimination because the fundamental driving force behind AI systems is data. Organisations need to ensure the data privacy of their customers and employees (Lee, Kwon and Pati, 2019). On the other hand, it is also necessary to ensure no bias or discrimination in the underlying data (Keding, 2020).

2.5 Measuring firm performance

Today, firm performance has become a relevant concept in strategic management research and is often used as a dependent variable (Taouab and Issor, 2019). Although it is a prevalent concept in the academic literature, there is little consensus on its definition and measurement. Due to the lack of an operational definition of corporate performance agreed by most scholars, different people will naturally propose different explanations based on their perceptions. *Table 2.5* summarises the definitions of other performances. Firm performance refers to an economic category that reflects a firm's ability to use materials and human resources to achieve its targets, which could include financial and non-financial targets (Zouaghi, Sánchez and Martínez, 2018). Noori *et al.* (2017) suggested that firm performance was valuable for managers to consider beyond gaining profits and shareholder returns, which are financial indicators to measure firm performance.

Firm performance in this paper is measured via two dimensions: financial indicators (ROA) and market indicators (Tobin's Q). ROA measures the financial aspects of a firm's performance, representing the ratio of net profit to total assets. Tobin's Q measures whether a firm is relatively overvalued or undervalued by simply calculating the market value divided by total assets. If Tobin's Q ratio for a firm is more significant than 1, it means the firm's market value is larger than the replacement value based on costs identified in the equity book.

Other indicators used to measure the market value of corporations include the capitalisation of shares, share prices and the number of shares outstanding, a market value estimated from equity return, etc. For example, Deane *et al.* (2019) suggested that a firm's market value was its market capitalisation, which is how much a company is worth on the stock market.

Table 2.5 Definition of variables

Title	Variable	Definitions and measures	Key references
AI focus	General definition	AI focus refers to focusing on specific domains that use cutting-edge technologies endowed by AI to support their operations, realise cooperative development and improve efficiency between employees and organisations (measured using the frequency of AI-related words in annual reports).	Albrecht, Rausch and Derra (2021) Fukuzumi <i>et al.</i> (2019) Chukwudi <i>et al.</i> (2018) Wamba-Taguimdje <i>et al.</i> (2020) Mishra, Ewing and Cooper (2022)
	Mechanical AI	The ability to learn and perform basic and repetitive tasks.	Grewal <i>et al.</i> (2020) Huang and Rust (2018, 2021) Dong <i>et al.</i> (2020)
	Thinking AI	The ability to perform analytical and intuitive tasks (reasoning-based AI).	Grewal <i>et al.</i> (2020) Huang and Rust (2018, 2021)
	Feeling AI	The ability to recognise human emotions and adapt behaviour accordingly.	Grewal <i>et al.</i> (2020) Huang and Rust (2018, 2021) Montes and Goertzel (2019)
Firm performance	General definition	Firm performance is a particular outcome obtained in management, economics and marketing. It provides the characteristics of competitiveness, efficiency and effectiveness for the organisation and its structural and procedural components through Pilot schemes, evaluation, efficiency, effectiveness and quality.	Verboncu and Zalman (2005) Bartoli and Blatrix (2015)
	Financial performance	Organisations implementing AI solutions have achieved improved financial and accounting performance, such as increasing revenue and reducing costs.	Alshahrani <i>et al.</i> , (2023) Davenport and Ronanki (2018)

	Market performance	AI technology can strengthen customer segmentation by processing and learning from existing customer data, allowing enterprises to understand customer preferences and lifestyles in a new way.	Chintalapati and Pandey (2022) Enholtm <i>et al.</i> (2021)
Specific variables that represent firm performance	ROA	The ratio of net profits to total assets	
	TBQ	Tobin's Q measures whether a firm is relatively overvalued or undervalued by simply calculating the market value divided by the total assets.	
Mediator	R&D general definition	R&D is defined as the processes and practices businesses use to gather knowledge to discover ways to improve their existing products and services or create new products. The condition of R&D can be measured by the ratio of R&D staff as a share of all the employees (RDD) and by investment in R&D as a share of the sales (RDI).	Viberg and Eslami (2020)
	RDD	The ratio of R&D staff as a share of all employees (RDD).	Viberg and Eslami (2020) Wang (2011)
	RDI	Investment in R&D as a share of sales (RDI).	Viberg and Eslami (2020) Wang (2011)
Moderator	EDU	Top manager education level (EDU).	Ho and Kuvaas (2020) Liu <i>et al.</i> (2020)

Table 2.8 represents different literature sources and various components that made them relevant to this study. Whether in the field of marketing or management and business, AI technology is developing rapidly. In *Table 2.8*, a comprehensive summary of the development of significant areas of AI in recent years can be seen. These include real-time price optimisation (Davenport *et al.*, 2020), sentiment analysis (Ma and Sun, 2020), churn analysis (Loureiro, Guerreiro and Tussyadiah, 2021) and talent acquisition (Makarius *et al.*, 2020; Raisch and Krakowski, 2021). The impact of AI application potential in various fields is also considerable, covering merchandising (Pillai, Sivathanu and Dwivedi, 2020), supply chain management (Toorajipour *et al.*, 2021), customer management (Ma and Sun, 2020; Pillai, Sivathanu and Dwivedi, 2020), market research (Huang and Rust, 2022, B; Li *et al.* 2021), enhanced resilience (Bag *et al.*, 2021), faster decision-making (Shrestha, Krishna and von Krogh, 2021), greater creativity (Mikalef and Gupta, 2021) and superior performance (Lin *et al.*, 2020; Ma and Sun, 2020). Therefore, AI is increasingly important for enterprises, and its impact on marketing and management is far-reaching (Davenport *et al.*, 2020). However, studies that explicitly examine AI's efficiency or performance impact focus on large samples are lacking.

2.6 Literature review on the role of R&D and executive education (EDU)

2.6.1 The role of R&D

R&D plays a crucial role in driving technological innovation and economic growth. Griliches (2007) pointed out that R&D investment not only directly promotes a company's innovation capability but also enhances the technological level of the entire industry through spillover effects. In addition, Cohen and Levinthal (1990) proposed the "absorptive capacity" theory, emphasising that enterprises can better absorb external knowledge and technology through R&D activities, which further enhances the innovation efficiency and competitiveness of enterprises. However, the role of R&D is not limited to directly influencing technological innovation. Aghion *et*

al. (2009) found that R&D can also indirectly affect the innovation performance of enterprises and industries by promoting knowledge sharing and collaborative innovation. This intermediary role is particularly evident in high-tech sectors, where knowledge-intensive R&D activities have become an essential driving force for innovation.

Rapid AI technology development and application require continuous improvement and optimisation to enhance product performance and functionality. By increasing R&D, AI companies can drive the development of new technologies, optimise existing algorithms, and develop new AI application scenarios, thereby significantly improving product competitiveness and market acceptance. The following is a list of research literature on the mediating role of R&D, such as Griliches (2007) study, which pointed out that R&D activities directly promote the development and market application of innovative products by enhancing technological commercialisation capabilities. In the field of AI, this means that through the intermediary role of R&D, AI companies can continuously launch more advanced and intelligent products to meet the constantly changing market demands.

Giménez *et al.* (2019) found that R&D human capital is crucial in enhancing a company's innovation capability and competitiveness. In AI companies, high-quality R&D teams can continuously drive the exploration of technological frontiers and the implementation of innovative applications, laying a solid foundation for the company's long-term development. Chiesa (1996) found that by constructing international R&D teams and implementing globalisation strategies, companies can leverage innovation resources from different countries and regions to enhance their competitiveness in the global market. In the AI industry, this means that through cross-border R&D cooperation and enhanced market adaptability, companies can better meet the needs of global customers and expand market share.

In addition, Liang and Li's (2022) study explores how digital transformation can

enhance R&D capabilities to promote innovation performance in manufacturing enterprises. Research has found that with the widespread application of digital technology in the manufacturing industry, enterprises need to strengthen their R&D capabilities to meet the challenges of market competition and technological progress. Specifically, digital transformation not only improves enterprises' production efficiency and supply chain management but also brings new innovation opportunities and market expansion possibilities to enterprises. These innovation opportunities and market advantages often depend on whether enterprises can effectively utilise their R&D capabilities to drive the development of new technologies and products. Diéguez Soto and Martínez Romero (2019) studied the impact of family business management participation on product innovation, emphasising the mediating role of R&D strategy in the innovation process of family businesses.

However, the above literature did not directly study the mediating role of R&D in the relationship between artificial intelligence and company performance. However, this literature provides rich research perspectives and empirical analysis, helping to deepen the understanding of the mediating role of R&D in different industries and environments. The mediating role of R&D in enterprises is multifaceted: from technological innovation to market adaptability, from talent reserves to the improvement of global competitiveness, all of which demonstrate the importance of R&D for the long-term success of enterprises. Through empirical research in the above literature, we can gain a deeper understanding of the mediating role of R&D at different levels, providing essential references and guidance for the research in this thesis.

2.6.2 The role of EDU

Executive education plays a crucial role in modern enterprise management. With the intensification of global competition and the promotion of technological progress, the quality and ability of corporate executives have a profound impact on the

development and performance of enterprises. Executive education helps executives improve their leadership and decision-making abilities by providing systematic management training and professional knowledge. Research has shown that executives who receive excessive quality management education can better understand and respond to market changes and effectively lead teams to achieve corporate strategic goals (Finkelstein, 1992; Sipahi & Timor, 2010).

Executive education not only enhances individual abilities but also profoundly impacts organisational learning and innovation. By learning new management concepts and best practices, executives can promote knowledge sharing and the establishment of an innovative culture within the organisation, thereby enhancing the competitiveness and flexibility of the enterprise (Hitt *et al.*, 1998; Zollo & Winter, 2002). Executive education directly affects the implementation effect of corporate strategy. Those executives with a good educational background are able to design and execute strategic plans more effectively, improving the efficiency of resource allocation and the accuracy of decision-making, thereby optimising corporate performance (Hambrick & Mason, 1984; Carpenter *et al.*, 2004).

For example, Saidu, (2019) studied the impact of CEO education background on the performance of Chinese companies. They found that the educational background of executives not only directly impacts the formulation of corporate strategies in academic and professional fields but also indirectly regulates the company's performance by influencing executives' cognitive and decision-making abilities. Sarto and Saggese (2022) studied the curvilinear relationship between board industry expertise and innovation investment, as well as the moderating effect of CEO education background. Research has shown that the CEO's educational background can significantly influence the board's ability to promote corporate innovation through new technologies, thereby affecting company performance.

Yang & Jin (2024) studied the moderating effect of executive education on the relationship between digital transformation and the manufacturing environment, social responsibility, and corporate governance (ESG). This study found through empirical analysis of Chinese A-share listed companies from 2010 to 2019 that digital transformation has promoted ESG performance in the manufacturing industry. The survey results showed that the education level of senior management teams, CEO tenure, and diversity of professional backgrounds moderated this relationship, thereby improving company performance. They pointed out that by enhancing executives' understanding and leadership skills in digital technology and innovation strategies, executive education can effectively promote innovative performance in the digital transformation process of enterprises.

This literature indicates that executive education is not only the transmission of knowledge and skills but also the enhancement of strategic execution and organisational learning abilities, thereby strengthening the competitive advantage of enterprises in the fiercely competitive market. Therefore, through this literature, we can see that executive education not only enhances the abilities and skills of individual executives but also promotes the improvement of strategic implementation and innovation capabilities at the entire enterprise level.

2.7 Artificial intelligence, EDU, R&D and firm performance

2.7.1 Artificial intelligence, EDU and firm performance

With the development of the global economy and the intensification of competition, companies in various countries have put forward higher requirements for the quality and capabilities of their executives. As the leaders and decision-makers of an enterprise, executives determine the development direction and performance of the enterprise to a large extent. Executive education background is integral to corporate leadership and impacts the company's strategy formulation and execution. Studying the relationship between a company's AI focus and its performance through the

education level of executives can help companies better select executive talents and increase the company's attention to and adoption rate of AI.

Many studies in the previous literature explore the relationship between executive education level and firm performance. Still, very few studies exist on the relationship between AI focus and the education level of executives (top managers). This thesis empirically studies whether a top manager's education level has a moderating effect on the relationship between AI focus and firm performance. As the decision-makers and executors of corporate strategy, the senior management team make strategic choices that directly affect firm performance. In today's era of rapid development and complex internal and external environments, AI technology is crucial to enterprises. Executives with an adventurous spirit will actively use new AI technologies, innovative management and strategic decision-making to improve the competitiveness of their companies.

Research by Hambrick and Mason (1984) shows that higher education-level executives have more robust innovation capabilities and better breakthrough thinking. With executive teams that are better equipped with these characteristics, the performance of companies is often better than that of rivals in the same industry. Sitkin, Sutcliffe and Schroeder (1994) show a significant positive correlation between the education level of CEOs of U.S. listed companies and company performance. Tihanyi *et al.* (2000) conducted an empirical study from the perspective of corporate growth. They found that executive teams with higher average education levels tended to collect better and more effective information faster before making decisions, thereby formulating strategies that were more conducive to the development of the enterprise so that the enterprise could show better performance. However, Gottesman and Morey (2006) studied the impact of educational characteristics on fund performance and found that obtaining master's and doctoral degrees had little impact on fund performance.

Previous research has focused primarily on the relationship between executives' education levels and firm performance. These studies generally show that executives with higher academic qualifications and professional backgrounds tend to be better able to lead companies to achieve good performance. There may also be differences in the impact of executive education background on firm performance in different countries and regions. In order to bridge this gap, this study uses the level of executive education in China as the background to explore in depth whether the level of executives' education has a moderating effect on the relationship between AI focus and firm performance. It provides an important reference point and inspiration for improving the level of enterprise innovation management and whether senior executives play a decisive role in AI technology adoption.

2.7.2 Artificial intelligence, R&D and firm performance

R&D is defined as the processes and practices by which businesses gather knowledge to discover ways to improve their existing products and services or create new products (Viberg and Eslami, 2020). Companies have an R&D sector to undertake the responsibilities of auditing the latest technologies, meeting the demands of consumers in the marketplace and exploring the possibilities of updating previous operations to better fulfil the requirements of target customers with updated products and services (Lee, Kwon and Pati, 2019). Xu and Zeng (2021) summarised the benefits of R&D to explore firms' motivations for performing R&D in their operations; it was considered an inexpensive way of generating new ideas, products and services for customers, and a way of exploiting opportunities for cost reduction in corporations, improving brand reputation with advanced technologies to appeal to and satisfy target customers, gaining improved profits and competitive advantages.

On the one hand, AI is related to technological innovation, which requires R&D investment by corporations. Chowdhury *et al.* (2022) suggested that investing in AI projects in R&D practices could have better financial outcomes than investing in

other technologies, based on investing and studying the U.S. Department of Defense SBIR Projects, which are developed for SMEs. Chen and Chen's (2022) findings showed that AI was related to technological innovation when firms gained intellectual capital by developing AI. They suggested that firms should invest in R&D to improve their intellectual capital in using AI and to achieve the additional benefits of improved operational performance. Lee, Kwon and Pati's (2019) findings confirmed that R&D investment and operational excellence were the top two factors leading to improved corporate performance. Zhao *et al.*'s (2021) findings suggested that R&D investment in improving employees' knowledge of innovations could improve their R&D alliance network and organisational innovation performance; however, if corporations allocated their R&D investment to generate employees' improved knowledge, improved organisational innovation performance should also be audited and the risky environment considered to establish whether they could result in improved financial performance and competitiveness in the marketplace.

On the other hand, some other studies examine the relationships between R&D and firm performance concerning the roles of R&D staff and the R&D department (Braganza *et al.*, 2021; Chowdhury *et al.*, 2022; Prentice and Nguyen, 2020; Wang *et al.*, 2021a). A higher level of R&D talent in corporations can act as a mediator by improving the efficiency of their use of current AI-related facilities to support improved firm performance. Besides investing in R&D, the ratio of talent in R&D as a share of the corporation's total number of employees suggests the capabilities that the corporation could effectively apply to AI-related technologies. Chowdhury *et al.* (2022) indicated that more employees working in the R&D department of corporations could support various tasks related to R&D practices in corporations, including the use of AI, which mostly requires staff in the R&D sector to apply new technologies. Prentice and Nguyen (2020) suggested that staff in the R&D department could use AI as a valuable tool to support operations, which could result in improved sales and profits for corporations.

The employee structure acts as a mediator to suggest how AI adoption in the corporation relates to the corporation's performance. Wang *et al.* (2021a) indicated that corporations benefited from accelerating AI focus, which could be achieved through the collective efforts of managers and employees in corporations, especially the staff in the R&D sector. A higher ratio of R&D staff as a share of all the employees suggests that corporations have more talent to support measures adopting AI, contributing to improved performance in the operations. Braganza *et al.* (2021) and Wang *et al.* (2021) highlight the significant roles of productive employment in supporting AI focus towards the excellent performance of corporations. The theory that explains the role of employee structure in influencing firm performance is an organisational learning theory, which suggests that firms adopting AI as a form of advanced technology in operations need the learning and promotions of the employees (Wang, 2011). A higher proportion of employees in the R&D department of a corporation suggests that senior managers can quickly introduce AI-related technologies to operations, indicating improved performance in operations.

R&D will boost firms' long-term performance by helping them to create new knowledge and expand the scope of their knowledge base, as well as improving the capability to absorb and integrate existing knowledge. Nonetheless, R&D activities are not without risk and may not always yield superior future performance (Liao and Rice, 2010). Therefore, it is crucial to analyse the impact of R&D on company performance by examining AI focus. For example, innovative AI products and services may not truly achieve the goal of meeting market demand. In addition, they may lead to higher costs and management challenges. New technologies may also bring unexpected challenges and may even be commercially unfeasible. They may also face strong opposition and ridicule from the market, especially on social media platforms. The R&D investment in product development and the salaries of many R&D personnel may exceed the company's revenue, leading to R&D expenses becoming sunk costs (Hsu *et al.*, 2013). To bridge this gap, this study explores the

moderating role of R&D in the relationship between AI focus and corporate performance. This study adds knowledge to AI technology adoption, transformation efficiency and management. It suggests that managers consider the company's R&D investment and R&D personnel ratio when paying attention to AI technology.

2.8 Chapter Summary

To summarise this chapter, the literature review and the summary in *Table 2.8* provide a basis for comprehending the concepts and theoretical frameworks around AI and how it affects the performance of businesses. Critical viewpoints on organisational strategy and adaptation are offered by the theories of talent management, DCs and economic theory. The conversation around AI explores its many technologies, capacities, adoption, application and areas of organisational emphasis. In addition, the firm performance outcomes of AI will be witnessed in those aspects. The following chapters' empirical research is built by synthesising various ideas and concepts connected to AI. Along with highlighting these theories' shortcomings and detractors, the study also emphasises the need for a nuanced understanding in the context of AI and corporate success. All in all, the chapter has established the framework for the study issues and theories that are examined in the following chapters.

Table 2.8 Overview of critical artificial intelligence publications in business literature

Publication	Definitions (AI)	AI focus domain	Aim/ Objectives	Key Constructs	Key theories/ Views	Methodologies	Findings	Implications
2022								
Huang and Rust (2022) <i>Journal of Retailing</i>	“AI is machines that mimic human intelligence computationally and digitally, designed to emulate (or surpass) capabilities inherent in humans, such as doing mechanical, thinking, and feeling tasks.” (p. 210)	AI in marketing	To develop a model for collaborative intelligence in marketing to address the critical issue of using AI to augment marketers and consumers at different intelligence levels.	-AI strengths (feeling, thinking, mechanical, analytical) -Human marketers’ and consumers’ strengths (feeling, biological, thinking, intuitive, mechanical contextual)	Multiple intelligences view	Conceptual	Develops a conceptual framework for collaborative AI in marketing	Introduces systematic guidance for firms and researchers to test innovative approaches to and boundary conditions of collaborative intelligence

Longoni and Cian (2022) <i>Journal of Marketing</i>	N/A	AI in marketing	To investigate AI in the hedonic and utilitarian attribute trade-offs and the word-of-machine effect.	-Word-of-machine -AI recommendations - Hedonic and utilitarian attribute trade-offs	N/A	Empirical	Word-of-machine influences attribute complexity, utilitarian goals	Provides a novel insight into understanding AI from the psychology of automation and human–technology interaction Explores the unanswered questions related to AI in hedonic/utilitarian trade-offs in consumer preference or resistance to AI recommenders
Mishra, Ewing and Cooper (2022) <i>Journal of the Academy of Marketing</i>	The capability of “machines to mimic Intelligent human behaviour.” (p. 2)	AI in marketing	To investigate the relationship between firms’ focus on AI in their 10-K reports and their gross and net operating efficiency.	-AI focus -Net operating efficiency (net profit per employee) -Gross operating efficiency (sales	-Economic theory -Marketing theory	Empirical A system of simultaneous equations test the model by using a 15-year period	-US-listed firms are in a state of impending transformation with regards to AI -AI focus	First to empirically work to test the effect of AI focus on firm performance Develops a new measurement

<i>Science</i>				per employee) -Return on sales -Return on marketing-related investment		(2005-2019) of 10-K data from 4,052 firms	influences the improvements of net profitability, net operating efficiency and return on marketing-related investment while reducing ad-spend and creating jobs	scale for AI focus
Volkmar, Fischer and Reinecke (2022) <i>Journal of Business Research</i>	“activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large” (p. 600)	AI in business	To review leading AI research in marketing To build themes and subordinate dimensions on AI in marketing.	Culture, strategy, and implementation Decision-making and ethics Customer management	N/A	Mixed-method including a Delphi study, as survey and two focus groups	-Explores the drivers and barriers to AI -Addresses the three distinct domains in AI	Provides a broader and deeper understanding of the human factor effects on AI in interdisciplinary perspectives via marketing, organisational behaviour, psychology and ethics

2021								
Bag <i>et al.</i> (2021) <i>Industrial Marketing Management</i>	N/A	AI in B2B marketing	-To explore the effect of Big Data-powered AI on customer, user, and external market knowledge creation to understand its impact on B2B marketing rational decision-making and influence firm performance.	-Big data -AI-enhanced knowledge creation in B2B marketing -Integrated AI -B2B marketing -Decision-making -Firm performance	-Knowledge management theory	-Empirical -Online Survey -South African Automotive Companies (219)	-Big Data-powered AI and the path to customer knowledge creation is significant. Big Data-powered AI and the path to user knowledge creation are significant. - Big Data-powered AI and the path to external knowledge creation is significant.	-It was observed that customer knowledge creation, user knowledge creation and external knowledge creation significantly affect B2B marketing and rational decision-making.
Balakrishnan and Dwivedi (2021)	N/A	AI in business	-To investigate the role of technology attitude and AI	-AI -Perceived anthropomorphis	-Technology acceptance model	-Empirical -Structural equation	-Perceived anthropomorphism plays the	-Bringing TAM and AI factors together to build a

<i>Annals of Operations Research</i>			attributes in enhancing purchase intention through digital assistants.	m -Perceived intelligence -Perceived animacy		modelling -Questionnaire (440)	most significant role in building a positive attitude and purchase intention through digital assistants.	conceptual model of digital assistants. -It built its argument about AI factors on the basis of psychology theories such as the uncanny valley theory, metacognitive theory, perception theories (theory of mind), development psychology, the theory of media equation, the three-factor theory of anthropomorphism, and the naive theory of intelligence.
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Guha <i>et al.</i> (2021) <i>Journal of Retailing</i>	N/A	AI in retail	-To examine how senior retailing managers should consider adopting AI, involving factors like the extent to which an AI application is customer-facing, value creation level, whether the AI application is online and ethics concerns.	-AI adoption -Customer-facing AI -Level of ethical concerns.	-Task-approach and endogenous growth theory	-Conceptual/Theoretical -Interviews with Senior Management	- A lot of value can be obtained by adopting non-customer-facing applications. The near-term impact of AI on retailing is substantial but may not be as pronounced as the popular press might suggest.	-Building on past research and from interviews with senior managers
Li <i>et al.</i> (2021) <i>Industry Marketing Management</i>	N/A	AI in management	To explore the interactive role of suppliers, customers and technology companies in the B2B market when they adopt AI.	-Customer experience value -System management capability Commercialisation-based capability -Interpersonal capabilities -Value of intra-and inter-organisational	-Value co-creation perspective -Service-dominant logic	Qualitative with 19 in-depth semi-structured interviews with three groups of B2B stakeholders in 6 firms -Thematic analysis	Identifies four types of value and three sets of capabilities and the interlinkages between them	Bridges three disciplines in the context of industrial AI development and usage

				-Learning -Function value				
Loureiro, Guerreiro and Tussyadiah (2021) <i>Journal of Business Research</i>	- Systems that think like humans - Systems that act like humans -Systems that think rationally -Systems that act rationally	AI in business	-Provide an overview of state-of-the-art research on AI in the business context and propose an agenda for future research.	-AI -Intelligent agent -Business applications -Text mining -Research agenda -Future trends	N/A	-Empirical review -Graph mining analysis -Text mining -Relevant studies (404)	-Findings reveal 18 topics classified into four main clusters: societal impact of AI, organisational effects of AI, AI systems, and AI methodology.	-Presents several main developmental trends and the resulting challenges. This includes robots and automated systems, the Internet of Things and AI integration, law, and ethics, among others.
Luo <i>et al.</i> (2021) <i>Journal of Marketing</i>	N/A	AI for Sales	Firms are exploiting AI coaches to provide training to sales agents and improve their job skills.	-AI coaching -AI aversion, information overload -New technology -Sales training -Sales force management	N/A	-Empirical -Experiments -Three randomised field experiments in two fintech companies	-To quantify the heterogeneous effects of AI coaches on agents' performance. -Redesigned AI coaches to solve	-AI coaches to train agents and improve their sales skills and performance more effectively and efficiently. -AI coach will not

							the challenges bottom- and top-ranked agents face.	have bad days or toxic emotions in the repetitive sales job training compared with human managers.
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Mishra and Pani (2021) <i>Journal of Information and Knowledge Management Systems</i>	N/A	AI in Business	-To explore impact as a value driver for the firms and help them get an operational and competitive advantage.	-AI -Analyses a time-tested -Firms' operating efficiency	-Organisational learning theories	-Conceptual/Theoretical	-Builds the link between learning and ambidexterity to propose paths for exploration and exploitation of AI.	-Integrates more than three decades of strategy and information systems literature to answer questions about value creation from AI. -The study extends the ambidexterity literature with contemporary research.
Perez-Vega et al. (2021) <i>Journal of Business Research</i>	"every aspect of learning or any other feature of intelligence can, in principle, be so precisely described that a machine can be made to simulate	AI in Service	-To explore how this type of technology can improve automated service interactions between the firm and its customers.	-AI -Online customer engagement behaviours -Stimulus-organism-response -Information processing systems	-Stimuli-Organism-Response theory	-Conceptual/Theoretical	-Integrative the linking of two bodies of research, customer engagement and AI	-Provides a theoretical contribution to the marketing literature by "integrating".

	it (p. 1)							
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Shrestha, Krishna and von Krogh (2021) <i>Journal of Business Research</i>	N/A	AI in Business	-Conceptualise decision-making process (e.g. in marketing, finance, operations, HR and strategy) -Augmented with DL Algorithm outcomes as deep learning-augmented decision-making.	-Explaining AI's inner workings. -Decision-making -Deep learning -Examine how DL applied to unstructured data may benefit managerial decision-making.	Deep learning (DL)	-Conceptual/Theoretical -2 case studies -Datasets from European e-commerce company Zalando and movie review aggregator site Rotten Tomatoes	-Deep learning (DL) algorithms promise benefits for decision-making within organisations	-Assisting employees with information processing, thereby augmenting their analytical capabilities. -Help employees transition to more creative work.
Shumanov, Cooper and Ewing (2021) <i>European Journal of Marketing</i>	N/A	AI in advertising	-To demonstrate the application of an algorithm using contextual data to ascertain consumer personality traits. -To explore the factors impacting the relationship between personality traits and advertisement persuasiveness.	-AI predicted personality	-Natural language processing	-Quantitative -Empirical use of two Studies -Banking customers (35,264) -Mixed Methods	- Matching consumer personalities with consistent advertising messages can lead to more effective consumer persuasion for most personality types.	-Building on advances in natural language processing. -Enabling the identification of personality from language. -Understanding purchasing behaviour based on the most dominant

								personality trait.
2020								
Campbell <i>et al.</i> (2020) <i>Business Horizons</i>	“The broad class of technology developed to collect data in order to solve problems or make decisions.” (p. 3)	AI in innovation	-Explain how AI can enhance the marketing function across nine stages of the marketing planning process.	-AI in marketing. -Marketing performance -AI application -Operational performance -Big Data Analytics	-Reinforced learning -Supervised learning	-Conceptual/Theoretical -Australian marketers (65)	-To seek to consolidate the growing body of knowledge about AI in marketing	Early adopters will likely be organisations with a solid digital base and a higher propensity to invest in AI.
Dubey <i>et al.</i> (2020) <i>International Journal of Production Economics</i>	N/A	AI in R&D	-To develop and test a model -To describe the role of entrepreneurial orientation in adopting Big Data analytics powered by AI and operational performance.	-Big Data Analytics -AI -Entrepreneurial orientation -Operational performance -Supply chain management -PLS SEM	-Dynamic capabilities theory -Contingency theory	-Empirical -Survey PLS-SEM Analysis -United States manufacturing firms (256)	Dynamic capability view and contingency theory to better understand the organisation's dynamic capabilities.	Provide empirical evidence based on data that EOs are more associated with higher-order capabilities.

Wamba-Tagui mdje <i>et al.</i> (2020) <i>Business Process Management Journal</i>	“AI means the use of technological devices aimed at reproducing the cognitive abilities of humans to achieve objectives autonomously, taking into account any constraints that may be encountered.”	AI in business	-Analyse the influence of AI on firm performance, notably by building on the business value of AI-based transformation projects.	-Firm performance (at the organisational and process levels) -AI -Business value (moderator)	-The theory of IT capabilities	-Qualitative, 500 case studies from IBM, AWS, Cloudera, Nvidia, Conversica, Universal Robots websites, etc., 2018-2019	-Adopting AI provides opportunities to improve the efficiency of their ecosystem -To optimise their strategic and competitive advantages with the improved automation, information and transformation effects.	-AI as a set/combination of IT configurations in various business areas. Multiple vital elements must be combined to ensure the success of AI: data, talent mix, domain knowledge, critical decisions, external partnerships, and scalable infrastructure.
2019								
Agrawal, Gans and Goldfarb (2019)	N/A	Economics of AI	How AI substitutes capital for labour in prediction tasks and may indirectly affect decision tasks	-Automating prediction tasks -Prediction in legal services	Decision-making	Conceptual/Theoretical	-It is not yet possible to know the net impact on decision tasks	-To highlight the usefulness of thinking in terms of prediction tasks and decision

<i>Journal of Economic Perspectives</i>			by increasing or decreasing the relative returns to labour versus capital.	-Substituting capital for labour in prediction tasks. -Creating new decision tasks.			-Whether existing or new, it is likely to favour labour or capital.	tasks, where decision tasks are perfect complements to prediction tasks.
Caputo <i>et al.</i> (2019) <i>Management Décisions</i>	N/A	AI in innovation	-To investigate the relations among soft skills, information technologies, and Big Data to build a possible bridge linking human and technology dimensions to increase firm performance.	-AI -Big Data management -Soft skills -High-tech European firms -Human resource management	-Employee training -Talent management	-Quantitative, - Uses structural equation modelling (SEM) 2017-2018 -human resources (4758) -High-tech European firms (72)	-Shows the existence of solid relations between some elements of human resources' personality, such as work motivation, social competencies and the firms' economic performance. - Mediated effect of firms' investment in Big Data in the relations between	-Underline the need to pay more attention to human resources' ability to organise work processes and activities. -Developing instruments and processes. -Need for developing tangible instruments to stimulate human resources' work motivation.

							human resources' organisational behaviour and the firms' economic performance.	
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CHAPTER THREE: THE INFLUENCE OF STATE POLICY ON AI AND CORPORATE GOVERNANCE OF LISTED COMPANIES

3.0 Introduction

This chapter discusses China's development and impact in the field of AI. Section 3.1 provides a brief introduction to the background of AI development in China. Section 3.2 discusses the literature on AI and its impact on performance in China, and section 3.3 describes how China differs from other countries in terms of AI development.

3.1 A brief introduction to the background of AI development in China.

The development of AI technology and AI-orientated industry cannot be separated from the fast-growing digital revolution after the end of the Second World War. According to Qiu (2016), AI technology refers to using computers to endow machines with intelligence abilities similar to that of the human race. The development of AI is regarded as a milestone of modern science and technology.

The development of AI in China can be traced back to the 1950s when basic research began in China. Famous institutions such as the Chinese Academy of Sciences and Tsinghua University conducted early AI research during this period, laying the foundation for later development (Qiu, 2016). With time, especially in the early 21st century, the Chinese government began to realise the strategic importance of AI and adopted a series of policies and measures to promote its development (Wu *et al.*, 2020). The most important of these is the "Made in China 2025" plan, which regards AI as one of the critical technologies and sets development goals and timelines to accelerate the process of intelligence and modernisation in China's manufacturing industry (Wübbeke *et al.*, 2016). In 2017, the Chinese government released the "National Development Plan for the New Generation of AI", which clarified the strategic direction and policy support measures for the development of AI in the coming years (Wang, Lu and Zeng 2007). This plan emphasises the government's

guiding role, actively promoting the research and application of AI technology through funding, policy support, and market-oriented innovation incentives (State Council of China, 2017a).

In addition, China's development in the field of AI is also heavily driven by technology giants. Companies such as Baidu, Alibaba, and Tencent have accelerated the commercialisation process of AI technology through extensive investment and acquisition actions. These companies not only invest heavily in core technology research but also actively explore and apply the potential of AI in various industries, such as intelligent transportation, smart healthcare, and financial technology (Lundvall & Rikap, 2022). Regarding ethics and regulatory environment, China is also striving to balance the development of AI technology with the protection of social ethics. Despite challenges in data privacy and security, the Chinese government has begun to strengthen its supervision of data security and gradually improve relevant legal and regulatory frameworks to address the challenges brought by AI technology (Roberts *et al.*, 2021).

3.1.1 Government support and policy

The Chinese government has played a vital role in promoting AI development, technological innovation, industrial upgrading, and economic transformation through policies and measures.

Firstly, in 2017, the Chinese government released the National Development Plan for the New Generation of AI. This milestone document clarifies the strategic direction and critical areas for the development of AI in the coming years. The plan emphasises strengthening basic research, accelerating breakthroughs in key core technologies, promoting the integration and development of AI and the real economy, and proposes various policy measures such as financial support, policy incentives, and legal and regulatory guarantees (State Council of China, 2017a). Secondly, the Chinese government supports the development of AI enterprises through funding and tax

incentives. For example, the government has established special funds to support the research and application of AI technology, encourage enterprises to innovate in key technological fields, and provide tax incentives to reduce research and development costs and market development pressure for enterprises (Colvin *et al.*, 2022).

In addition, the government has strengthened talent cultivation and the construction of scientific and technological innovation platforms. The Chinese government has actively promoted talent cultivation and the transformation of scientific and technological achievements by establishing research institutes in universities, constructing AI innovation parks, and promoting industry-university research cooperation, laying a solid foundation for the long-term development of the AI industry (Arenal *et al.*, 2020). In terms of ethics and regulations, the government is also actively exploring and formulating relevant policies to ensure the legitimacy and sustainability of the development of AI technology. The Chinese government has introduced a series of laws and regulations in data security, privacy protection, and AI ethics to regulate and guide the application of AI technology, prevent the risks of technology abuse and data leakage (Roberts *et al.*, 2021). In summary, the Chinese government actively promotes the innovation and application of AI technology through comprehensive measures such as policy support, financial investment, and legal protection, helping China's competitiveness in the global AI field to improve continuously.

3.1.2 Support from technology giants

Chinese technology giants such as Baidu, Alibaba, Tencent, and others have played a crucial role in promoting the development of AI technology. These companies have accelerated China's competitiveness in the global AI field by investing in research and development, acquiring innovative companies, and applying technology in multiple industries.

Firstly, as a leading AI company in China, Baidu is committed to achieving significant breakthroughs in areas such as speech recognition, image recognition, and natural language processing (NLP). For example, Baidu's AI open platform and Baidu Brain project provide developers and businesses with rich AI tools and solutions, driving technological innovation and application practices in the industry (Li, 2020). Secondly, Alibaba has accelerated the application of AI technology in the business sector through its research institution, DAMO Academy, and strategic investments in cloud computing, the Internet of Things (IoT), and the digital economy. Alibaba's urban brain project and intelligent logistics system demonstrate the potential of AI in the urban management and logistics industry (Wu *et al.*, 2020). Thirdly, Tencent is actively exploring the application of AI technology in content recommendation, personalised services, and intelligent customer service based on its vast user base in the social media and online entertainment industries. The research achievements of Tencent's AI laboratory and research institute in the fields of speech recognition, machine translation, and virtual reality have promoted the commercialisation and popularisation of AI technology (Mao & Shi-Kupfer, 2023).

Therefore, these technology giants not only invest a large amount of funds and human resources in technology research and development but also promote the healthy development of the entire ecosystem by opening up innovation platforms, strengthening industry cooperation, and incubating innovation projects. Their collaboration with the government and academia has further promoted China's global leading position in the field of AI technology (Xu *et al.*, 2024).

3.1.3 Ethical and regulatory landscape

China is facing ethical and regulatory challenges and explorations in the development of AI, striving to balance the relationship between technological innovation and social ethics (Cheung, 2018). Firstly, the Chinese government is gradually strengthening regulation and policy-making in AI's ethical and regulatory aspects. In 2017, China

released the "Development Plan for the New Generation of Artificial Intelligence", which includes guiding principles for AI's ethics and social responsibility. These principles aim to ensure AI technology's fair, transparent, and secure application while avoiding the risks of technology abuse and data privacy leakage (State Council of China, 2017a).

Secondly, China is strengthening its regulatory framework in data privacy protection. With the development of big data and AI technology, data privacy and information security have become increasingly important issues. The Chinese government has strengthened regulations on the collection, use, and storage of personal data by formulating laws and regulations, such as the Personal Information Protection Law, in order to protect the individual privacy rights and interests of citizens (Roberts *et al.*, 2021). In addition, China has taken multiple measures to promote transparency and accountability in AI technology. The government encourages enterprises to establish and improve the transparency and interpretability of AI algorithms to ensure fairness and trustworthiness in the decision-making process. Meanwhile, strengthening the review and supervision of AI systems to ensure their compliance with ethical and legal requirements is an essential component of China's regulatory environment (Cai, Chen and Zhang, 2020; Qiao-Franco & Zhu, 2024).

3.2 Literature review on AI and its impact on China's economic performance

The rapid development of AI technology has profoundly impacted the global economy. As one of the largest AI markets in the world, China's application and implications are particularly significant. This section will review the role of AI in the Chinese economy and its specific impact on economic performance, exploring its role in improving production efficiency, promoting innovation, changing labour market demand, and promoting industrial structure transformation.

3.2.1 Economic impact

The widespread application of AI technology in the Chinese economy has profoundly impacted various aspects, including economic growth, production efficiency, industry structure, and changes in the labour market. Firstly, introducing AI technology has significantly improved China's production efficiency. Research has shown that through the application of automated and intelligent production processes and machine learning algorithms, the production efficiency of China's manufacturing industry has been significantly improved, thereby reducing costs and improving product quality (Cioffi *et al.*, 2020). Secondly, AI has been crucial in driving China's economic growth. Enterprises and industries investing in AI technology, such as cloud computing, big data analysis, and intelligent manufacturing, not only drive the development of related industrial chains but also promote overall economic growth. The widespread application of these technologies, especially in the service industry and emerging technology fields, has provided new impetus for the structural transformation and conversion of old and new driving forces of the Chinese economy (Wu *et al.*, 2020).

Thirdly, the impact of AI technology on the Chinese labour market is increasingly evident. Although the widespread application of AI may lead to a decrease in some traditional job positions, it also creates new job opportunities and demands, such as a sharp increase in demand for highly skilled positions such as data scientists, AI engineers, and intelligent system developers (Zhou *et al.*, 2020). Finally, the widespread application of AI technology drives the adjustment and upgrading of China's economic structure. For example, the introduction of intelligent manufacturing and intelligent logistics systems is changing the operation mode of traditional manufacturing and logistics industries, promoting digital transformation and intelligent upgrading of industries (Li *et al.*, 2017). In summary, the application of AI technology in the Chinese economy has profoundly impacted production efficiency, economic growth, labour market, and industrial structure transformation,

providing new impetus for the sustained development of the Chinese economy and enhancing global competitiveness.

3.2.2 Social and cultural influence

The widespread application of AI technology in Chinese society and culture has had multiple impacts on social structure, cultural cognition, and individual lifestyles. Firstly, the promotion of AI technology has promoted the intelligence and convenience of social services. For example, introducing intelligent voice assistants, AI customer service, and intelligent city management systems has improved the efficiency and quality of public services and residents' living experience (Wang, Teo & Janssen, 2021). Secondly, the application of AI in the fields of education and culture has driven innovation in educational methods and cultural production models. The development of virtual reality technology, personalised learning systems, and intelligent education platforms has provided new opportunities for the balanced allocation of educational resources and personalised learning, promoting the digital transformation of the cultural industry (Huang, 2021).

Thirdly, popularising AI technology has profoundly impacted the social structure and labour market demand. Although the automation of AI may lead to a reduction in some traditional job positions, it also creates new job opportunities and demand, such as an increase in highly skilled professions such as data analysts, AI engineers, and intelligent technology application experts (Zhou *et al.*, 2020). Finally, the application of AI technology in the cultural industry and creative economy has promoted the innovation of cultural products and the transformation of communication methods. Using AI to generate art, intelligent, innovative tools, and intelligent marketing systems, China's cultural industry has faced challenges and opportunities in the digital age, promoting the diversified development of cultural creativity (Zhao *et al.*, 2023). Therefore, the application of AI technology in China's social and cultural fields has profoundly impacted public services, education, cultural industries, and social

structure, injecting new impetus into the intelligent transformation of society and the innovation of cultural ecology.

3.2.3 Technical progress

The rapid development of AI technology has profoundly impacted China's technological innovation, industrial upgrading, and technological progress, promoting technological innovation and efficiency improvement in multiple industries. Firstly, the application of AI technology in China's manufacturing industry has promoted technological progress and productivity improvement. By applying intelligent manufacturing, automated production lines, and machine learning algorithms, China's manufacturing industry has improved product quality, production efficiency, and industrial safety standards, promoting manufacturing development towards intelligence and high-end (Chang *et al.*, 2021). Secondly, AI has played a crucial role in technological innovation and the development of emerging industries. For example, in the fields of cloud computing, big data analysis, AI chips, and the Internet of Things technology, Chinese enterprises have accelerated the commercialisation and marketisation process of new technologies through continuous research and development investment and technological innovation, driving continuous breakthroughs in the forefront of technology (Allen, 2019).

Thirdly, the popularisation and application of AI technology have driven the development of the digital economy. Through data-driven decision support systems, intelligent market analysis tools, and personalised recommendation systems, China's digital economy has experienced rapid growth and significant achievements in fields such as e-commerce, financial technology, and digital media (Chen, Teng & Chen, 2022). Finally, the widespread application of AI technology has promoted the formation of interdisciplinary technology integration and innovation models. Chinese technology enterprises and research institutions have collaborated in fields such as AI, biotechnology, and materials science, promoting technological progress and

cross-industry innovation and laying a solid foundation for future technological development (Mariani *et al.*, 2023). In summary, the technological progress of AI technology has had a profound impact on multiple aspects of the Chinese economy, promoting industrial upgrading, technological innovation, and rapid development of the digital economy, providing a strong impetus for China to maintain its leading position in global technological competition.

3.2.4 Education and research impact

The application of AI technology in China's education and research fields has profoundly impacted academic research, educational models, and talent cultivation, promoting innovation in higher education and the transformation of scientific research achievements. Firstly, the application of AI technology in education has promoted the balance of educational resources and the development of personalised learning. Promoting intelligent education platforms, virtual reality technology, and personalised learning systems has improved the quality and effectiveness of education, bringing new teaching models and management methods to the education industry (Xu & Samikon, 2024). Secondly, the application of AI in scientific research and academic research has promoted innovation and transformation of academic achievements. Through data-driven scientific research decision support systems, intelligent scientific research analysis tools, and automated experimental platforms, Chinese research institutions and universities have accelerated the research process, promoted the commercial application and technology transfer of scientific research achievements (Liu *et al.*, 2020).

Thirdly, popularising AI technology has driven the transformation of talent cultivation models and demand for high-end talent. The demand for highly skilled talents such as AI engineers, data scientists, and intelligent system developers is rapidly increasing. China's higher education institutions and vocational training institutions are actively adjusting their curriculum and education models to cultivate professional talents that

meet the needs of the new economic era (Knox, 2020). Finally, the application of AI technology in the fields of education and research has promoted the deepening of international cooperation and academic exchanges. Chinese higher education institutions collaborate with global research teams and academic organisations to carry out joint research projects, jointly exploring the potential and challenges of AI in educational innovation and scientific progress (Knox, 2020). Hence, the widespread application of AI technology in China's education and research fields has promoted innovation in education models, the transformation of scientific research achievements, and the optimisation of talent cultivation models, injecting new impetus into the international competitiveness of China's higher education and the sustainable development of scientific and technological innovation.

3.3 The development of AI in China and international differences

Due to China's unique regulatory environment, strategic government intervention, and cultural attitude towards technology, the development of AI in China significantly differs from that of Western countries. Firstly, China's regulatory environment has high concentration and flexibility, allowing the government to quickly formulate and implement policies conducive to AI development. Secondly, the Chinese government has taken active strategic intervention, promoting the rapid growth of AI technology through extensive investment, policy support, and national strategic planning. Finally, Chinese society has a high acceptance and adaptability to technology, and its tolerant attitude towards new technologies has provided a good foundation for the popularisation and application of AI. However, in contrast, the development of AI in Western countries relies more on market-driven and corporate innovation, with relatively less government intervention and a more complex and strict regulatory environment. At the same time, Western society pays high attention to privacy protection and ethical issues, which has created certain constraints on the promotion and application of AI. Therefore, there are significant differences in the development paths and models of AI between China and Western countries. Below, I will provide a

detailed explanation of the situation from four aspects.

3.3.1 Government intervention and strategic planning

Firstly, the Chinese government has clarified the critical position of AI as a national strategic emerging industry through formulating and implementing strategic plans. For example, China has formulated strategic documents such as "Made in China 2025" and the "National Development Plan for the New Generation of AI", clarifying the development priorities and policy support measures in areas such as intelligent manufacturing, intelligent transportation, and intelligent healthcare (State Council of China, 2017; State Council of China, 2017a; Ministry of Industry and Information Technology of China, 2020). Secondly, the Chinese government actively promotes the research and application of AI technology through financial investment and policy support. Establish special funds, tax incentives, and technological innovation bases to support innovative activities of enterprises and research institutions in AI hardware, algorithm research, and application development (Hine & Floridi, 2024; Chang *et al.*, 2021).

Thirdly, the Chinese government has also been essential in promoting international cooperation and AI technology standard-setting. By participating in international standard setting, conducting international cooperation projects, and promoting international technological exchanges, China has played an increasingly important role in the global development of AI, facilitating the process of global AI governance and cooperation (Wang *et al.*, 2023). Finally, the Chinese government also attaches great importance to constructing an ethical and legal framework for AI technology. It has formulated guiding principles and relevant laws and regulations on AI ethics to guide and regulate the development and application of artificial intelligence technology and safeguard public interests and social stability (Roberts *et al.*, 2021). So that the Chinese government has effectively promoted the development and application of AI technology in various fields through intervention and strategic

planning, providing solid support for China to gain an advantage in global AI competition.

3.3.2 Data privacy and ethics

With the rapid development of AI technology, data privacy protection and ethical issues have become important issues in the development of AI in China. China has taken multiple policy measures in data management and ethical framework construction to balance the relationship between technological development and public interest. Firstly, the Chinese government has strengthened its supervision and legal system construction for data privacy protection. The “Personal Information Protection Law” and other relevant laws and regulations have been formulated, clarifying the standards for the collection, storage, processing, and transmission of personal data and strengthening the responsibilities and obligations of data processing entities (National People's Congress of China, 2021; Ministry of Industry and Information Technology of China, 2022).

Secondly, the Chinese government has promoted the development and promotion of data and AI ethics guiding principles. By establishing an ethical evaluation mechanism, promoting corporate self-discipline, and conducting public education, the ethical awareness and sense of responsibility in applying AI technology have been strengthened, promoting the harmonious development of AI and social values (Xin-Wei and Gang, 2022). Thirdly, China actively participates in developing global data governance and AI ethical frameworks on the international stage. China has proposed the concept of "data sovereignty", advocating for safeguarding national and individual data security and rights in global data governance, actively participating in relevant discussions and formulating international standards in international organisations such as the United Nations (Daly *et al.*, 2019).

Finally, the Chinese government encourages AI enterprises to balance technological innovation and data security protection. By establishing technology research and

development bases, funding security technology research, and promoting best practices, we support enterprises in strengthening their management and control of data privacy and ethical issues while encouraging technological innovation (Calzada, 2022). China attaches great importance to data privacy protection and ethical issues in the development of AI and strives to find a suitable balance between technological innovation and social ethics through laws and regulations, ethical guidance principles, international cooperation, and technological innovation, promoting the sustainable development of AI.

3.3.3 International cooperation and competition

Firstly, China actively promotes international cooperation and strengthens scientific and technological exchanges and collaboration with other countries and international organisations. By participating in international conferences, signing bilateral agreements, and supporting cross-border scientific research projects, China has promoted technology sharing and international transformation of innovative achievements in the field of AI (Xinsong, Guoning and Yu, 2011). Secondly, China has adopted a multi-level strategy in the global competition for AI, enhancing the country's influence in technological innovation and market competition. Through government-supported international investment and mergers and acquisitions, the establishment of international research and development centres, and the introduction of foreign high-end talents, China has strengthened its technological competition and cooperation with developed countries and emerging markets (Allen, 2019).

Thirdly, China's role in the global governance of AI is increasingly prominent, and the concept of data sovereignty and digital governance has been proposed. China advocates safeguarding the rights and interests of countries and individuals in the global data flow, promoting consensus among the international community on data security, privacy protection, and AI ethics, and promoting relevant agendas in international organisations such as the United Nations (Roberts, Hine & Floridi, 2023).

Finally, Chinese enterprises have also played an essential role in the international market, expanding the international influence of AI products and services through independent innovation and technological output. For example, Chinese Internet giants and technology companies have performed well in technological innovation and market expansion in the field of AI, becoming key players in global competition (Wübbecke *et al.*, 2016). China has continuously expanded its technological innovation and market influence in the development of AI through international cooperation and competition, injecting vitality into the global growth of AI and playing an increasingly important role on the international stage.

3.3.4 Cultural and social factors

Firstly, China's traditional cultural values have impacted the development of AI. For example, China values collectivism and social stability, which are reflected in the application of AI technology, emphasising the direction of technology serving society and promoting social welfare. Unlike Western countries that emphasise personal privacy and freedom, China places greater emphasis on balancing technological innovation and social sharing in the development of AI (Huang, 2021). Secondly, the acceptance and attitude towards AI in Chinese society vary among different groups. Urban residents and young people are usually more open and accepting of new technologies. They are more willing to accept the application of AI in daily life, such as smart homes, intelligent transportation, etc. In contrast, rural areas and the elderly population may have lower levels of acceptance of AI technology, resulting in information asymmetry and differences in their ability to use it (Umair *et al.*, 2021).

Thirdly, the Chinese government and enterprises actively promote public education and technology popularisation when promoting AI technology. By organising training courses, promoting application cases, and conducting science popularisation activities, we aim to enhance the public's understanding and recognition of AI and promote more active participation and support for the development of AI technology (Xu &

Samikon, 2024). Finally, China also pays attention to cultural diversity and social inclusivity in the development of AI. In the process of technical design and application, taking into account the differences in different regions, ethnic groups, and cultural backgrounds, corresponding technical standards and application guidelines are formulated to promote the popularisation and application of AI to better meet the needs of social diversity (Xia *et al.*, 2022). Therefore, cultural and social factors play an essential role in the development of AI in China, influencing the direction of technology application, public attitudes, and policy formulation. By understanding and responding to these factors, China can better promote the development of AI technology and achieve harmonious development between technology and society.

CHAPTER FOUR: CONCEPTUAL FRAMEWORK

4.0 Introduction

The conceptual framework of the thesis is summarised in *Figure 3*, which proposes the ratio of R&D staff as a share of all the employees and the investment in R&D as a share of the sales as mediators, and top manager education level as a moderator in the relationship between AI focus and firm performance. Based on the framework, this chapter then develops the hypotheses for the whole study.

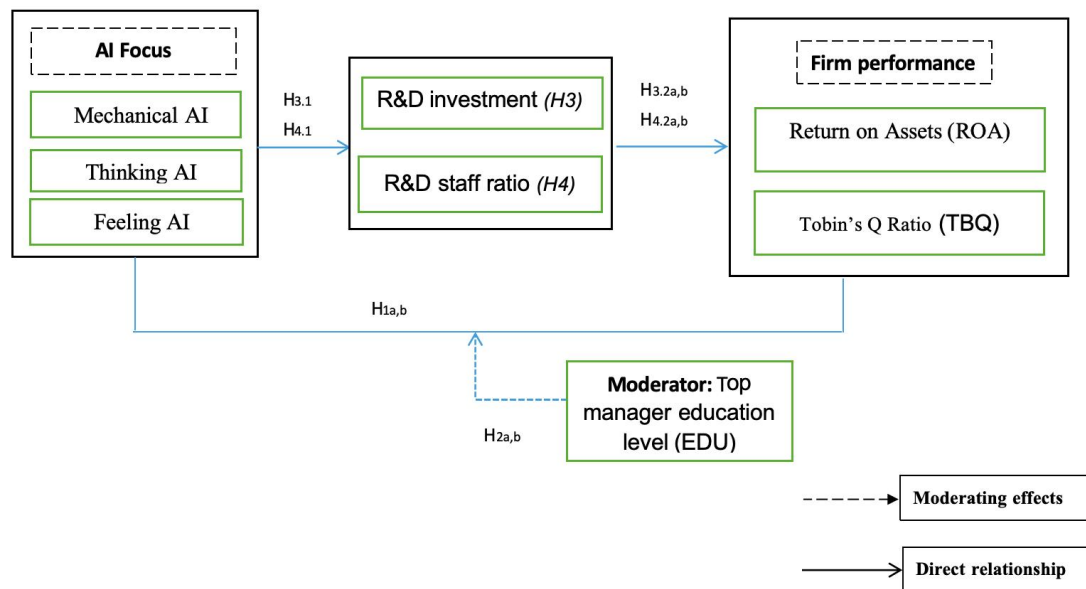


Figure 3. AI focus – conceptual framework of model

4.1. AI focus and firm performance

The study adopts managerial economics under economic theory (Kahneman & Tversky, 1979) to understand the relationship between AI focus and firm performance. Based on this theory, enterprises can achieve a sustainable competitive advantage based on a reasonable consideration of innovation strategies and wise decision-making in response to changes in the enterprise's micro-ecosystem that affect the enterprise's capabilities and profitability (Hirschey & Pappas, 2010). In the role of artificial intelligence in innovation management, this perspective is used to adjust corporate strategies to cope with new changes brought about by additional

expenditures on artificial intelligence technology and an increase in the proportion of R&D personnel.

It is increasingly difficult for enterprises to survive in today's globalised, complex and ever-changing business environment. Due to the increasing technological disruptions and fierce competition from other countries, such as the United States and India, businesses must react quickly. However, adopting new technical innovations often implies significant changes in firms' available strategies, which call for rational judgment of the change and its potential consequences for firms' usual management (Pannell, 1996). According to economic managerial theory, firms should adopt rational policies when embracing disruptive technologies, demanding systematic demonstration of the feasibility of the change strategy.

Managerial economics offers an ideal approach to analyse the reasonable behaviour of firms regarding trustworthy and transparent choice of firm strategies and decisions (Chinowsky & Byrd, 2001). According to managerial economics, a firm should be cautious in evaluating the potential adverse outcomes when deciding to execute crucial changes in the management and operational processes of new technologies (Israelsen & Rohde, 2007). The use of AI is no exception and is assumed to be a change in the original way of firm management. Adopting any new technology assumes a potential risk that requires a firm to be prudent. This is responsible for firms to protect the benefits of the stakeholders.

Scholars have explored how AI is related to firm performance by studying and critically discussing the relationships from different perspectives. Some studies directly examine the roles of AI in influencing firm performance (Luo, 2022; Mishra, Ewing and Cooper, 2022; Wamba-Taguimdje *et al.*, 2020). For instance, Mishra, Ewing and Cooper (2022) examined the links between firms' focus on AI and their gross and net operating efficiency, concluding that an AI focus on operations improved firm performance. The findings suggested that US-listed firms achieved

their transition to AI since net profits, net operating efficiency, and return on marketing-related investments were enhanced by the use of AI because of the reduced number of positions and lower labour costs. However, the increased attention to AI will negatively correlate with overall operational efficiency (sales per employee).

Luo (2022) suggested that using AI was one primary method for corporations to improve the efficiency of their enterprise network innovation and firm performance. The study examined the roles of deep learning and the Internet of Things to identify how technological advances created opportunities for corporations to collect mass data to understand their customers' unique needs and achieve better service. However, adopting AI also implies a violent change in crucial strategies for firms, especially in reallocating business resources among different departments. AI focus often means significant changes in new investments related to the technical training of employees with AI skills, the purchase and maintenance of new equipment, and the extra expenses to recruit more R&D staff (Wamba-Taguimdje *et al.*, 2020). According to the managerial economics theory, all these imply increased **management and operational risks** for firm development. **For example, reallocating budgets, manpower, and time, such as resource restructuring, may lead to the risk of resource shortages or decreased operational efficiency in some departments. Providing AI skills training to existing employees requires time and financial investment and carries the risk of uncertain training outcomes. In addition, purchasing and maintaining new hardware and software equipment may come with higher additional cost risks. There is also a human resource risk of increasing the search for suitable talents and the need to hire more R&D personnel with AI skills.**

Wamba-Taguimdje *et al.* (2020) studied how AI influenced firm performance by exploring the business value of AI-based transformation projects. The study led to the finding that adopting AI provided firms with opportunities to improve the efficiency of their ecosystems and optimise their strategic and competitive advantages with improved automation, information, and transformation effects. Improvements for

firms with supportive AI could include the financial perspective, marketing and administration, and systems.

Melynchenko (2020) responded to concerns over whether or not AI could help determine an organisation's financial robustness. AI is more successful than humans at modelling financial risk and even bankruptcy potential. Companies that integrate AI may better assess and predict their financial security compared with those that do not employ AI. AI tends to improve each application and continuously learns on its own account, exceeding initial projections. Firms that employ AI will post more effective assessments than those that do not use AI.

In addition, Königstorfer and Thalmann (2020) focused on using AI in commercial banks. AI can help reduce lending costs and losses and enhance security when handling payments. It can also help improve compliance processes and refine customer targeting, leading to improved organisational efficiency. Banks can harness AI to lower the cost of labour and operations. Integrating AI into productivity can help banks achieve an optimum return on equity by using the fewest assets to generate significant profits.

Although these studies have emphasised the positive role of AI in stimulating firm performance, other research indicates a negative relationship between them. For example, Lui, Lee and Ngai's (2022) study, which was based on the analysis of 119 announcements from 62 publicly listed firms that had invested in AI, found that AI investments had a detrimental effect on the market value of these firms. The findings revealed that on the day of the announcement, the stock prices of these firms experienced a decline of 1.77%. Notably, non-manufacturing firms and those with limited IT capabilities or lower credit ratings suffered a more pronounced negative impact compared with their counterparts. The findings by Lui *et al.* (2022) indicate that investors generally perceive announcements related to AI investment as unfavourable news for a significant portion of firms.

Similarly, Rana *et al.* (2022) found a dark side of AI in upgrading firms' competitiveness. They collected data from 355 operational, mid-level and senior managers representing diverse service sectors and organisations of various sizes in India. The outcomes revealed that an absence of effective governance, subpar data quality, and inadequate training of crucial personnel contribute to the opacity of integrating AI and business analytics. This opacity, in turn, initiates suboptimal business decision-making and a heightened perception of risk, ultimately leading to operational inefficiencies, further hindering the firms' competitiveness. The results indicated that AI was not always as positive as imagined, and the costs generated by AI implementation could play a substantial role in causing negative sales growth and employee dissatisfaction, thereby creating a competitive disadvantage for the firm.

Therefore, from the above scholars' findings, it can be seen that the application of AI to enhance the firm's performance is challenging. That is also the reason why many scholars (e.g. Agrawal, Gans and Goldfarb, 2018; Li *et al.*, 2019; Mishra, Ewing and Cooper, 2022; Roumani, Nwankpa and Tanniru, 2019) have put forward the argument that it is a challenge for corporations to successfully apply AI because they fail to create improved business value unless they can incorporate AI effectively into their ecosystems in order to support their operations. Roumani, Nwankpa and Tanniru (2019) identified that enterprises in the software industry showed a higher likelihood of failure than businesses in other industries, mainly because of the risky status of technologies applied by the industry, such as AI, to support operations. Their findings suggested that technological issues mattered in improving the introduction of AI to software corporations to achieve improved financial performance, requiring managers to focus on the reliability and availability of advanced technologies within the capabilities of employees, financial resources and corporate strategies. Enterprises in other industries also need to take notice of the impacts of different AI technologies on firm performance by identifying the mechanisms by which AI exerts an impact on firm performance.

Li *et al.* (2019) studied using interpretable machine learning models to support machine learning algorithms and innovative efficiency in corporations. The findings identified four categories of businesses based on their different business models and the available AI technologies, suggesting that the fit between the business models and the AI technologies was the most critical factor for constructing and improving the ecosystem of their operations and moving towards gaining competitive advantages. Moreover, corporations using AI technologies to achieve enhanced performance should set up a decision-making system to align their corporate strategies, the resources available, and the alternative AI technologies from which they can choose. The effect of AI's focus on directing corporations' operations might also impact other aspects of the operations and performance besides the operational efficiency of corporations (Chiles *et al.*, 2021). For example, R&D investment in AI could improve the operational efficiency of corporations while also meaning additional costs for the corporations, especially in the short run, requiring scholars to assess both the benefits of improved operational efficiency and the costs of the additional investments when they evaluate the overall financial performance benefits gained by being AI focused. Therefore, the role of AI in enhancing firm performance depends on many factors, and generally, the prospects of AI will be positive once organisations have overcome those barriers. On this basis, from the perspective of management economics theory in economic theory, the following hypotheses are proposed:

H1: AI focus negatively influences firm performance, as assessed by (a) accounting metrics (return on assets) and (b) market metrics (Tobin's Q ratio).

4.2 AI focus and firm performance with senior managers' education level as the moderator

This study proposes that top managers' education level (EDU) acts as a moderator in the relationship between AI focus and firm performance. Managers are responsible for corporations implementing AI applications intended to support improved firm performance. Accordingly, it is suggested that EDU plays a moderating role in the

relationship between AI focus and firm performance. This depends on whether the firm has the resources to implement AI. Firm operators need to understand the relevant skills and knowledge gaps before applying AI, which is still in the early stages of development. Given the high level of “hype” around AI, it is essential to separate fact from fiction. The ability to develop AI differs from having the money/resources to implement it. The fact that a firm has an idea does not mean that it will be able to develop it successfully. The level of resources available to a firm can indicate its commitment to innovation. If firms have the resources, their AI idea may more likely come to fruition. This is an essential consideration for firms looking to invest in AI.

TMT helps explain the roles of senior managers in supporting the improved operations of corporations, such as by promoting the efficiency of implementing AI in corporations to support improved firm performance (Dubey *et al.*, 2020; Takanashi and Lee, 2019; Wamba-Taguimdje *et al.*, 2020). TMT believes that the education level of senior management can improve workplace efficiency, thereby enhancing performance. Takanashi and Lee (2019) agreed that corporate leaders played a role in supporting resource allocations and in supporting the use of AI technologies towards improved performance. Corporations wishing to achieve excellent performance should develop their managers' and leaders' skills and capabilities, such as via AI-based transformation projects (Wamba-Taguimdje *et al.*, 2020). TMT confirms the role of employee training in improving the skills and performance of staff.

Previously, scholars did not consider the education of corporate directors as a moderating factor when studying the relationship between AI focus and corporate performance. However, some studies have shown that the role of education is vital, as it can improve the skills and abilities of managers, thereby improving the efficiency of using artificial intelligence technology in enterprises (Ho *et al.*, 2022; Kousaridas *et al.*, 2014; Liu *et al.* (2020). Liu *et al.* (2020) suggested that AI supported technological innovation by referring to panel data analyses of China's manufacturing

sectors and suggesting that educated senior managers in corporations could successfully support corporate efficiency in adopting AI. The study used empirical modelling and logical reasoning to suggest that AI supported technological innovation, based on the industrial robot data offered by IFR (Increased Frequency Reporting) concerning 14 manufacturing industries in China from 2008 to 2017. The findings showed the mechanism of how AI contributed to technological innovation by identifying the roles of educated managers who undertook the responsibilities of adopting AI to support the corporations' technological innovation. The findings suggested that educated managers and employees accelerated knowledge creation and enabled corporations to enjoy the technology spillover effect.

Kousaridas *et al.* (2014) confirmed the roles of educated managers in supporting corporations using AI towards improved performance, suggesting that education was a moderator linking AI and improved organisational performance because education improved managers' efficiency in operations and management practices. Their work also introduced the self-growing concept to study the topology optimisation of corporations. The findings suggested that managers' absorptive and learning capabilities via increasing talent investment and R&D in corporations improved the organisations' efficiency in using networks and achieving enhanced organisational performance. Ho *et al.* (2022) agreed with the role of education as a moderator to promote improved efficiency and performance when educated managers could gain the capabilities of learning by doing, which suggests the continuous improvement of managers when applying AI in operations.

Apart from the direct impacts, several studies have explored the indirect influences of executive education on firm performance. Danneels (2002) investigates how the cognitive structures of top management teams, including their educational backgrounds, affect a company's innovation capabilities and performance. The study shows that a diverse educational background among executives can moderate the company's innovation strategies, which is particularly crucial in the context of AI

integration. Christopher & Holweg, (2011) emphasise the importance of strategic resources, including top management education, in moderating the relationship between governance structures and performance outcomes in global supply chains. This research is significant for understanding how the educational background of top managers influences strategic decisions and operational results, which is vital for comprehending the role of AI in strategic governance.

Carpenter *et al.* (2004) reviewed the development of research on top management teams and emphasized how the diversity of top management team members (including educational backgrounds) affects organizational strategic choices and performance. The study provides insights into how the different educational backgrounds of executives influence company strategies choices. This is particularly relevant for understanding how the educational diversity of top executives moderates AI-driven strategies. Redondo and Cambra Fierro (2008) investigate how educational levels moderate the long-term orientation of supply relationships and their impact on business results. The findings suggest that higher educational levels among top managers can lead to more effective long-term strategic planning and relationship management. This is crucial for firms to integrate and utilise AI technologies successfully.

Mengli and Yongming (2020) analyse how executive education and tenure influence ambidextrous innovation, especially in balancing exploration and exploitation strategies. The study demonstrates that executives with advanced educational backgrounds are better equipped to leverage high technology for both incremental and breakthrough innovations, thereby enhancing overall firm performance. Sarto and Saggese (2022) examine the curvilinear relationship between board industry expertise and innovation input, with CEO education acting as a moderator. The research indicates that a CEO's educational background can significantly influence the board's ability to foster innovation through AI, thus impacting firm performance.

In conclusion, although these studies do not directly address AI, they provide theoretical support for understanding how executive education shapes strategic decisions, governance structures, and, ultimately, the application and impact of AI technologies within organisations. Therefore, empirical research investigating the moderating role of executive education on the relationship between AI and firm performance is urgently needed.

However, corporations that regard the education level of managers as a moderator in implementing AI to promote organisational performance face costs and potential risks (Farrokhi *et al.*, 2020; Rana *et al.*, 2022). Rana *et al.* (2022) identified the dark side of AI to suggest that educated managers might result in higher levels of risks and more costs in corporations towards their operational efficiency when the managers were motivated to introduce riskier AI technologies. Farrokhi *et al.* (2020) suggested that educated managers moderated the efficiency of using AI to detect crisis-facing organisations and improve operational efficiency by studying AI in the B2B context. Furthermore, highly educated managers may be trapped in the problem of over-confidence and over-reliance on their own judgments while ignoring or underestimating the fundamental challenges in implementing AI projects in organisational contexts, as Brock and Von Wangenheim (2019) pointed out. This could restrict the company's AI capability because of its short-sightedness in forecasting the possible risks, dangers, and obstacles of AI implementation in order to foster organisational success (Camerer, 2018).

As AI technology, as a new innovation, requires a manager's open mind and innovative thoughts to promote the further implementation of the projects, well-educated managers may over-rely on past work experience because of the expertise already gained. This hinders their capability to adjust themselves to new technology. Some studies (e.g. Larrick and Feiler, 2015; Ameen *et al.*, 2022) have shown that some senior managers can be more inclined to adopt conservative managerial methods in order to sustain their managerial success, and they often lack a

risk-taking spirit to try new models in the implementation of innovative items like AI technology. Therefore, while a high level of knowledge among senior managers contributes to understanding technology and the business environment, highly educated managers may encounter difficulties driving innovation and implementing emerging technologies. This could consequently weaken their role when seeking to enhance firm performance by promoting the effectiveness of AI.

Therefore, based on the above content, the study seeks to deepen understanding of how top manager education level (EDU) moderates the relationship between AI focus and firm performance. Although some studies have indicated that EDU poses potential negative impacts in moderating the relationship between AI focus and firm performance, the majority have shown that EDU can commonly perform as a positive moderator to positively moderate the relationship between AI focus and firm performance. Therefore, the present study assumes that a positive moderating role is played by EDU, i.e. that the negative relationship between AI focus and firm performance is mitigated if senior managers have a higher education level, resulting in the following hypothesis:

H2: In the presence of a higher top manager education level, AI focus is associated with a less negative impact on firm performance measured by (a) accounting indicators (ROA) and (b) market indicators (Tobin's Q ratio).

4.3 AI focus and firm performance with R&D as a mediator

In addition to exploring the relationships between AI focus and firm performance and the moderating effect of EDU, the research investigates the mechanisms by which AI focus is related to firm performance with R&D investment and R&D staff ratio as mediators because the development and successful implementation of AI requires the supportive status of R&D investment and the R&D staff ratio. The study thus addresses the relationship between AI focus and R&D since AI is related to technological innovation, which requires R&D investment and high R&D staff ratios

in corporations.

Dynamic capabilities theory (DCT) (Daneshvar Kahkhi and Palvia, 2016; Eisenhardt and Martin, 2000; Teece, Pisano and Shuen, 1997; Collis 1994) also explains the effects of R&D on firm performance to indicate a potential mediating role of R&D in the relationship between AI focus and firm performance. This relates to the ability of firms to integrate, build and reconfigure internal and external capabilities to address the changing business environment. DCT extends RBV theory, which suggests that firms can gain competitive advantages over other businesses by gaining rare, valuable, non-substitutable and difficult-to-imitate resources and capabilities to support their operations (Wang, 2011). The types of resources required to support corporations in gaining competitive advantages include tangible and intangible resources, which are valuable for corporations to have at their disposal when designing and conducting their operations (Hossain *et al.*, 2022). For example, R&D investment can buy items that enable corporations to improve the scale of their production and to improve firm performance, such as enhanced ROA when firms can enjoy the benefits of economies of scale with the additional investments (Hossain *et al.*, 2022). Besides the tangible resources gained by corporations with higher R&D investment, there are other intangible assets and resources, such as technologies purchased by corporations with R&D investment. These types of intangible assets, combined with the various tangible assets, contribute to corporations gaining improved competitive advantages, such as improved reputation and brand value in the marketplace.

Mizik and Jacobson (2003) argue that superior firm performance resulting from competitive advantage emanates from superior customer value creation and value appropriation capabilities. Value creation is linked to R&D activities (Xiong and Bharadwaj, 2013). According to Andras and Srinivasan (2003), R&D is one of the critical inputs that should be effectively managed to compete successfully in the market. However, in the literature, the findings on the link between R&D and firm performance are inconsistent, with some indicating a solid relationship between R&D

and performance and others finding that R&D does not impact performance. Vanderpa (2015) conducted a study in the U.S., and Wang and Fan (2014) focused on listed firms in China. They found a notable impact of R&D on firm performance, especially for firms that relied on financed R&D. R&D investment was also cited as boosting stock returns (Rao, 2016; Wang *et al.*, 2017). On the other hand, Kendirli and Konak (2014) and Ayaydin and Karaaslan (2014) found no significant link between R&D and innovation and financial performance. Therefore, this study attempts to ascertain the nature of this relationship in the Chinese context using approaches that exploit rich data to assess short- and long-term effects. The study also distinguishes between firms that rely on financed R&D and those that do not (Ying *et al.*, 2018).

Empirical studies can be constructed by including R&D investment and employee structure (the ratio of R&D staff to all employees) as mediators to study the impacts of AI focus on the improved performance of corporations. This is because, on the one hand, improved R&D investment means improved value for customers, enhanced technological capabilities among employees and better capabilities in auditing and responding to future challenges based on historical data (Xu and Zeng, 2021). Still, on the other hand, a higher proportion of employees working in the R&D department suggests a greater level of talent supporting the business's ability to quickly adopt AI in operations (Xu and Zeng, 2021).

However, there are dynamics in the workplace, resulting in conflicts between staff in the R&D department and other departments, which influence the work efficiency of the R&D department and affect how the corporation can apply AI in supporting improved operational efficiency and improving financial performance (Wang *et al.*, 2021). For example, Lauzijs and Miliute (2020) found that in organisations, if the R&D department worked independently of other departments, it would lack the capability to cooperate with other relevant staff, e.g. the financial department and HRM departments, to smoothly and successfully launch AI programs. Moreover, the

actual effectiveness of how R&D may perform as a mediator in the relationship between AI implementation and firm performance also depends on the consistency between R&D managerial goals and the firm's overall strategic goals. Conflicts between the R&D department and overall organisational targets will create an impression of the role of R&D as negative, hindering the actual performance of AI technology in stimulating the performance of organisations (Xue, Fang and Dong, 2021). As demonstrated by Xue, Fang and Dong (2021), currently, the R&D structures in some sectors, such as the military domain, operate with a considerable degree of independence, leading to an imbalance in the advancement of AI technology across military and civilian applications. This asymmetry poses a potential obstacle to future AI technology innovation, which weakens the positive role of AI technology in fostering innovative performance in organisations. To promote more equitable progress of AI technology in the military and civilian domains, it is imperative to institute a novel organisational framework characterised by “integrated development” among R&D entities in both the military and civilian sectors.

Therefore, from the prior research findings, it can be assumed that, generally, R&D can play a positive role in mediating the relationship between AI focus and firm performance, but that on some occasions, the mediating role could be transformed to be negative. Based on this discussion, the following hypotheses are proposed:

H3: R&D investment mediates the relationship between AI focus and firm performance, as measured by accounting indicators (return on assets) and market indicators (Tobin's Q ratio).

H3.1: AI focus will affect the company's investment in R&D.

H3.2: Investment in R&D will affect firm performance measured by (a) return on assets and (b) Tobin's Q ratio.

H4: The R&D staff ratio mediates between AI focus and firm performance measured by accounting indicators (return on assets) and market indicators (Tobin's Q ratio).

H4.1: AI focus will affect the company's R&D staff ratio.

H4.2: The R&D staff ratio will affect firm performance measured by (a) return on assets and (b) Tobin's Q ratio.

The above extensive literature review has laid the theoretical foundation for this study, enabling the construction of a framework and the generation of eight hypotheses (see *Table 4.1*). This chapter has provided an overview of the basic principles supporting the research methods and, crucially, the development of the constructed measurement scale to support the testing of the proposed model.

Table 4.1 List of research hypotheses based on the research questions

Hypotheses and underpinning theory	
Question 2: What are the key influences of AI focus on firm performance?	
H1 (Economy theory)	H1: AI focus negatively influences firm performance, as assessed by (a) accounting metrics (return on assets) and (b) market metrics (Tobin's Q ratio).
Question 3: What is the moderating role of top managers' education level in the relationship between AI focus and firm performance?	
H2 (Talent management theory)	H2: In the presence of a higher top manager education level, AI focus is associated with a less negative impact on firm performance measured by (a) accounting indicators (return on assets) and (b) market indicators (Tobin's Q ratio).
Question 4: What is the mediating role of the R&D staff ratio and R&D investment in the relationship between AI focus and firm performance?	
H3 (Dynamic capabilities theory)	R&D investment has a mediating effect on AI focus and firm performance, which is measured by accounting indicators (return on assets) and market indicators (Tobin's Q ratio).
H3.1	AI focus will affect the company's investment in R&D.
H3.2	Investment in R&D will affect firm performance, as measured by (a) return on assets and (b) Tobin's Q ratio.
H4 (Dynamic capabilities theory)	The R&D staff ratio mediates between AI focus and firm performance, as measured by accounting indicators (return on assets) and market indicators (Tobin's Q ratio).
H4.1	AI focus will affect the company's R&D staff ratio.
H4.2	The R&D staff ratio will affect firm performance, as measured by (a) return on assets and (b) Tobin's Q ratio.

4.4 Chapter Summary

In summary, this chapter has proposed different hypotheses related to the research aims and objectives, setting out the whole research framework in preparation for the data collection and analysis. These hypotheses are proposed in line with the theoretical frameworks derived from management economics theory in economic theory, DCT and TMT. The following chapters present the methodology, research data and analysis of the results with further discussion.

CHAPTER FIVE: DATA AND METHODOLOGY

5.0 Introduction

This chapter discusses the research philosophy, methodology, design, data collection, and estimation methods. This explanatory longitudinal study uses quantitative analysis methods to explain (i) the relationship between AI focus and firm performance in Chinese listed companies, (ii) the mediating role of R&D in the relationship between AI focus and firm performance in Chinese listed companies and (iii) the moderating effect of top manager education level on the relationship between AI focus and firm performance in Chinese listed companies. To support the research aims and objectives, this chapter builds on the conceptual framework (Chapter 4) and explains the research methodology adopted to test the hypotheses proposed in the chapter.

Therefore, this chapter elaborates on the criteria for sample selection and data sources, providing a basis for identifying dependent and independent variables suitable for the research objectives. It will also discuss the rationale for using multiple regression techniques. Other components considered in this chapter include ethics, confidentiality, data validity, and the reliability of the research methods.

5.1 Market context

According to Stanford's 2021 AI index report, the number of citations in Chinese AI journals is more significant than that in the United States. In addition, according to the Research Report on China's AI Software and Application Market -2020, the scale of China's AI software market will reach 23.09 billion yuan in 2020, ranked second globally. Moreover, China is one of the leading global hubs of AI development and aims to become the global leader in AI by 2030 (Nathani, 2018). It has realised the economic potential of AI technology and considers it a significant part of building the country's innovation capacity. The Chinese government has encouraged firms to develop, control and use AI for future growth (Nathani, 2018). However, reaping the

benefits of AI relies on the actual degree of AI focus in Chinese listed companies, which requires them to develop strategic awareness and technical know-how and to overcome the costs of AI implementation (Barton *et al.*, 2017).

This study measures an enterprise's AI focus level based on text analysis. Based on the word frequency ratio of AI-related keywords in the annual reports of listed companies, this paper constructs variables to measure enterprises' level of AI focus. In 2005, the Guidelines for the Contents and Formats of Information Disclosure by Companies Offering Securities to the Public, revised by the China Securities Regulatory Commission, stipulated that listed companies should review their operations during the reporting period and look forward to future development. Therefore, if the management of a listed company regards AI as an essential part of its enterprise development strategy and formulates corresponding action strategies to realise enterprise automation and intelligent transformation, this major event will undoubtedly have a significant impact on the production, operation and future development of the enterprise's influences. Therefore, according to the annual report information disclosure principles of the China Securities Regulatory Commission, the greater the importance and implementation of the AI strategy, the more inclined companies will be to disclose information related to AI focus.

There are several important reasons why this research chose 2014 as the starting point year for the development of AI in China. Firstly, in 2014, the Chinese government began to vigorously promote the innovation-driven development strategy, creating a favourable policy environment for the development of AI technology. The government has introduced a series of policies, clarifying the strategic goals of technological innovation and promoting the research and application of AI. For example, the State Council (2016) Outline of the National Innovation Driven Development Strategy was officially released in 2016; its preparation and discussion process began in 2014 and was gradually implemented during this period. The outline clarifies the goal of making scientific and technological innovation the core strategy

of national development and promotes the core role of scientific and technological innovation in economic transformation (Agrawal, Gans & Goldfarb, 2019).

Secondly, in 2014, the Chinese economy shifted from high-speed growth to high-quality development, focusing on technological innovation and industrial upgrading. In this context, AI technology is regarded as an essential tool to promote industrial upgrading and economic growth. As a result, governments and enterprises have increased their investment in AI. For example, "Made in China 2025" was officially released in 2015, and its core ideas and direction were gradually established in 2014. This policy aims to promote the development of high-tech industries, including AI, enhance the level of intelligence in manufacturing, and promote economic structural transformation (Reshetnikova & Mikhaylov, 2023). So, choosing 2014 as the starting point can provide longitudinal insights over a longer time span and identify sustained patterns and long-term impacts. This is particularly important for understanding the role and impact of AI in the Chinese economy and society (Cave *et al.*, 2019).

In addition, significant technological breakthroughs were made in the global field of AI in 2014, particularly in applying deep learning technology. These technological breakthroughs have enhanced the application prospects of AI and influenced worldwide technology and investment trends. China has quickly responded to this trend and increased investment in research and development of artificial intelligence. For example, deep learning and Convolutional Neural Networks (CNN) (Schmidhuber, 2015), as well as breakthrough advancements in deep learning technology, such as the success of CNN in image recognition tasks, have significantly improved the application level of AI technology. These technological advancements have sparked global attention and investment in AI (LeCun *et al.*, 2015). Therefore, 2014 is a starting point covering key technological breakthroughs such as deep learning. It can track these technologies' applications and further development in

China, evaluating their driving role in the industry (Russakovsky *et al.*, 2015).

Finally, since 2014, China's investment in AI startups has significantly increased. The influx of venture capital and government funds has promoted the rapid development of AI enterprises, which are rapidly growing in technology research and development, application, and commercialisation (Jack, 2021). For example, since 2014, venture capital firms and government funds have significantly increased their investment in artificial intelligence startups, driving the establishment and development of a large number of AI companies. The influx of capital has accelerated the commercial application of artificial intelligence technology (CB Insights, 2019). Moreover, China's AI development can be compared with global trends to understand China's position and competitiveness in the global AI landscape (Anderlini, 2019).

5.2 Research design

The research design is the critical framework and overall structure established by the study, including the interrelationships between AI focus, R&D, top manager education level and firm performance. This study aims to draw inferences from the causal relationships between the variables to assess the direct relationship between AI focus and firm performance. Considering the availability of electronic database sources of accounting data, including the financial statements of listed companies published by the China Stock Market and Accounting Research (CSMAR) database and the Wind database, the researcher believes that the choice of a quantitative method is more appropriate than a qualitative method, as readily available secondary data in the form of absolute numbers and percentages can be utilised to interpret the study target.

In addition, based on the theoretical background and empirical evidence discussed in the literature review (Chapter 2), the researcher explores the causal relationship between the AI-focused variables, the enterprise-level variables and firm performance to achieve the following research objectives:

- To investigate the relationship between Chinese listed companies' AI focus (dividing AI into mechanical AI, thinking AI and feeling AI) and firm performance.
- To examine the mediating effects of R&D staff ratio and R&D investment on the relationship between AI focus and firm performance.
- To investigate the moderating effect of top manager education level on the relationship between AI focus and firm performance.

5.3 Sample and data collection process

Data were collected from two databases, the CSMAR database and the Wind database. The CSMAR database can be purchased from Shenzhen GTA Information Technology Co., Ltd. CSMAR is a leading Chinese language database jointly produced by the University of Hong Kong and GTA, which covers the governance and financial structure of listed companies in mainland China. The Wind database can be purchased from the Chinese information company Wind Information Co., Ltd., headquartered in Lujiazui, Shanghai. It provides various financial market data, such as stocks, bonds, futures, foreign exchange, securities, and other fields. The Wind database is widely used in fields such as financial market analysis, investment decision-making and risk management.

To obtain the final sample, the following restrictions were imposed:

1. ST (special treatment) and PT (particular transfer) stocks were excluded because extreme values will have an adverse impact on statistical results.
2. Firms with missing observations for any variable in the model between 2014 and 2022 were excluded.

The above restrictions led to an initial sample of 20,474 observations for the Shanghai and Shenzhen stock exchanges and a final sample of 2,318 listed companies.

The study examined the impact of AI focus on firm performance by taking panel data and using different statistical methods (ordinary least squares (OLS), fixed effects (FE)

and random effects (RE)). This study considers the A-share listed companies on the main board of the Shanghai and Shenzhen stock exchanges from 2014 to 2022 as the research sample. This paper chose to collect data from 2014 onwards because, since that year, China has implemented AI policy reforms that have improved the quality and accuracy of data. The study sample size is large enough (nine years of panel data and 20,474 firm-year observations) to allow the generalisation of the conclusions.

There are unbalanced panel data. Some missing data were collected from the financial accounting annual reports of the research objects, and the rest were gathered from websites included in the China Science and Technology Statistical Yearbook. Because data were collected from audited financial statements such as annual reports (PDF documents downloaded from the Wind database) and authentic databases, the reliability and accuracy of the data could be controlled. Annual reports were downloaded from the Wind database and the official websites of various companies. Python software was then used to count the frequency and ratio of AI keywords from the PDF text, which was then used to identify relevant text and frequency statistics. In addition, the financial data of listed companies were collected from the CSMAR database. Then, the data from the two databases were merged according to the company's listing code and year. The original panel data was obtained after cleaning the data with Excel software. Finally, the software STATA was used for statistical analysis.

5.4 Summary statistics of variables and measurements

The data collected represent quantitative micro-variables of 2,318 listed companies in China's A-share stock market; they are considered cross-sectional data of time series observations over nine years. The years with a significant amount of missing data on the variables required for the empirical test are eliminated from the sample, and thus, the final sample consists of 20,474 observations. This study uses the ratio of AI keywords in the annual report regarding the variables in terms of AI. In contrast,

keyword frequency with an alternate value of AI is used for the independent variables. As far as financial performance is concerned, the study used return on assets (ROA) and Tobin's Q ratio as dependent variables for measuring firm performance since they are accounting ratios usually used to measure the effective performance of management.

Institutional R&D with different compositions is used as a mediating variable, and top managers' education level is used as a moderating variable. Data on other control variables were also collected, as highlighted in *Table 5.4* and discussed in the data collection section.

Table 5.4 presents the sources and descriptions of all the study variables. This paper focuses on the relationships between AI focus, EDU, R&D investment, R&D staff ratio, and firm performance. According to the hypotheses put forward above, this paper mainly considers five types of variables: dependent, independent, mediating, moderating, and control variables. The detailed explanations of each variable are explored in the following subsections.

Table 5.4 Variables and measurements

Variable name	Symbol	Description	Definition of the measuring method	Sign	Theoretical justification	Data source
Dependent variables	ROA	Return on assets	Net profit/Total assets	-	Economic theory	CSMAR
	TobinQ	Tobin's Q ratio	Market value A/Total assets	-	Economic theory	CSMAR
Independent variable	AIR = (Mechanical AI ratio + Thinking AI ratio + Feeling AI ratio)	Artificial intelligence ratio	Statistics for AI word ratio from the company's annual report			Wind
Mediating variables	RD	R&D investment	Investment in R&D	+/-	Dynamic capabilities theory (DCT)	CSMAR
	RDD	R&D staff ratio	Number of R&D staff/Total number of employees	+/-	Dynamic capabilities theory (DCT)	CSMAR
Moderating variable	EDU	Top managers' (executives') education level	Highest education level of top managers (executives)	+	Talent management theory (TMT)	CSMAR

Control variables	SIZE	Asset size	Ln (total assets)			CSMAR
	ATO	Total asset turnover ratio	Operating income/Ending balance of total assets			CSMAR
	REC	Accounts receivable turnover ratio	Operating income/Ending balance of accounts receivable			CSMAR
	TOP	Concentration of ownership	Number of shares held by the top 10 shareholders/Total number of shares			CSMAR
	MV	Market value	Market value A = A share * current closing price A share current value + domestic listed foreign shares B share * current closing price B share current value (Shanghai * CNY_USD, Shenzhen/HKD0CNY, converted to RMB) + (total number of shares – RMB ordinary shares – domestic listed foreign shares B share) * (total ending value of owner's equity/paid up capital current ending value) + total ending value of liabilities for the current period			CSMAR
	GRO	Growth rate	Enterprise income growth rate			CSMAR
	LEV	Asset/liability ratio	Total liabilities/Total assets			CSMAR

Notes: economic theory; DCT , dynamic capabilities theory; TMT, talent management theory

5.4.1 Dependent variables (firm performance variables)

Firm performance refers to the results of an evaluation process and evaluation criteria: productivity, integration and institutionalisation (Price, 1968). This study uses Tobin's Q and return on assets as primary performance measures. The study estimates Tobin's Q as the equity market value divided by the assets' total value and ROA as the return on assets. Both performance measures have their advantages and disadvantages. For example, Dhamadasa *et al.* (2014) argue that accounting-based measures consider the company's historical and current financial position and assess the management's ability to effectively utilise the company's assets and any other given resources. Nonetheless, Morck, Shleifer and Vishny (1988) believe that the market-based Tobin's Q value can better reflect the value of corporate intangible assets. Therefore, the inclusion of multiple performance measures will reduce the limitations of performance accounting measures. An example is the market indicator Tobin's Q, which shows that managers or accounting policies do not manipulate a company's market performance, nor is it affected by limitations inherent in accounting statements.

5.4.2 Independent variable (AI focus variables)

The independent variable for this study is AI focus. This research uses text mining to uncover the annual report word ratio of the term AI. The study used the ratio of the mentions of AI-related words in annual reports as a variable, measuring the degree of focus on the company's AI. Specifically, the AI keywords were classified into three types, mechanical AI, thinking AI and feeling AI, depending on whether they have low or high intelligence (Huang and Rust, 2021). Mechanical AI offers the benefits of standardisation. Thinking AI provides personalisation benefits. Feeling AI delivers the benefits of relationalisation.

For mechanical AI, the following keywords were used: "Intelligent production", "Intelligent manufacturing", "Automation", "Artificial intelligence", "Self-service", "Robot", "Collaborative robots", "Robot delivery", "Drone delivery", "Service robot", and "Chatbot".

For thinking AI, the following search terms were used: “Pattern recognition”, “Speech recognition”, “Emotional recognition”, “Text recognition”, “Handwriting recognition”, “Face recognition”, “Object detection”, “Entity recognition”, “Algorithm”, “Text mining”, “Machine learning”, “Deep learning”, “Supervised learning”, “Reinforcement learning”, “Model performance”, “Model services”, “Model monitoring”, “Model validation”, “Model training”, “Data acquisition”, “Data processing”, “Artificial Intelligence Operations”, “Training data” and “Data pipeline”.

Finally, for feeling AI, the relevant keywords were as follows: “Natural language processing (NLP)”, “Natural-language understanding”, “Text to speech technology”, “Machine translation”, “Computer vision”, “Intelligent Image Analysis”, “Image processing”, “Neural network”, “Artificial neural network”, “Convolutional neural network”, “Predictive analysis”, “Customer analysis”, “Inferential analysis” and “Cognitive Services”.

While research on AI focus is growing, such as the present study, which uses textual analysis to examine annual reports focusing on specific keywords like “customer analysis,” “inferential analysis”, and “cognitive services”, it represents a reasonably recent mode. The current study offers a unique approach, considering that existing studies are likely to have focused on analysing AI patent filings or press releases; this method will provide fresh insights, although it requires solid justifications and validations.

In order to provide this justification, the keywords were divided and subdivided into three separate areas in which the company’s AI focus exceeds that of sheer adoption. Keywords such as sentiment analysis or the recommendation of systems belong to the customer analysis sections. The inferential analysis terms, such as predictive modelling or risk assessment, point to a focus on data-driven insights for informed decision-making. Finally, keywords such as cognitive services, natural language processing, or computer vision show investments in AI with cognitive capacities similar to human capacities used for improved automation and interaction between mankind and computers. These keywords are divided into mechanical AI,

thinking AI and feeling AI according to AI technology's low, medium and high levels of intelligence (Huang and Rust, 2018; Huang *et al.*, 2019). Mechanical AI offers the benefits of standardisation, for example, self-service robots to provide services. Thinking AI provides personalisation benefits, such as Netflix movie recommendations. Feeling AI delivers the benefits of relationalisation, such as customer complaints.

This classification helps investigate how various AI applications, not just general adoption itself, affect performance. The study puts forward a new approach that demonstrates the novelty of the research. Clearly, it explains why those keywords were selected and categorised in this way to enhance the research's credibility. This work provides valuable insights into how AI focus relates to firm performance, as the relationship is not always straightforward.

The study used the ratio of the number of times these terms are mentioned to measure a company's focus on AI. China's overall annual AI development level was considered an alternative variable in the robustness test. Specifically, AI keywords were used in the Baidu search engine index to represent the degree of attention paid by firms to AI.

5.4.3 Mediating variables

The most direct manifestation of the successful completion of R&D activities is the generation of R&D results. R&D results can be new materials, new products or new equipment. They can help enterprises develop new market areas, form their core competitiveness and increase their market share, thereby increasing the company's profit level. The results of completed R&D investment are mainly intangible assets represented by proprietary technologies and patents. At the same time, this study uses employee structure (R&D staff ratio) to describe the technical level of employees. This paper selects R&D investment and R&D staff ratio as the mediating variables.

5.4.4 Moderating variable

AI focus is part of corporate decision-making, and corporate decisions will be affected by management; therefore, this study believes that the background characteristics of senior executives will affect the relationship between AI focus and firm performance. Specifically, it is suggested that the higher the education level of executives, the more likely they are to choose AI technology, which will have a more significant promotion effect on performance. Senior managers' educational level (EDU) assigns educational level as follows: no education (below technical secondary school), vocational education (college or technical secondary school), undergraduate, master, doctorate, other and MBA. A bachelor's degree or above (i.e. university-level education) is considered a higher education level, so a university degree or above is regarded as a high level of education.

5.4.5 Control variables

The management and revenue status of an enterprise will change due to many factors, which also indicates that it is not only the variables studied in this paper that affect the performance of the enterprise but other factors, too. Therefore, interference from other factors must be controlled to keep the research results unbiased. To control interference by other factors in the research, overcome the errors caused by omitted variables, and more accurately analyse the relationship between AI and corporate performance, this study adds control variables from different dimensions such as company characteristics, financial status and corporate governance structure. These are explored in more detail in the following subsections.

5.4.5.1 Company size (SIZE)

Companies of different sizes operate differently. The size of a company reflects its governance level, profitability and operating risks to a certain extent. Therefore, this paper introduces it into the model to eliminate the impact of the scale effect. Sales, total assets, business volume and the total number of employees can all be used to measure the company's

size, so it is more reasonable to use total assets to measure this. Due to the large gap and high amount of assets of each company, this paper uses a logarithmic function to process the total assets of the company in order to reduce errors.

5.4.5.2 Total asset turnover ratio (ATO)

The total asset turnover ratio is an essential indicator for measuring a company's operating capabilities. It reflects the flow rate from raw materials entering the company to finished products being sold. Its calculation formula is operating income/ending balance of total assets. A faster turnover rate proves that the company's operational capabilities are higher, thus affecting corporate performance. Therefore, this research also uses it as a control variable.

5.4.5.3 Accounts receivable turnover ratio (REC)

Generally speaking, the higher the accounts receivable turnover ratio, the better. A high accounts receivable turnover rate indicates that the company collects accounts quickly, has a short average collection period, fewer bad debt losses, fast asset flows and strong debt repayment capabilities. Correspondingly, the lower the number of accounts receivable turnover days, the better. If the actual number of days it takes for the company to collect accounts exceeds the number of days for accounts receivable stipulated by the company, it means that the debtor has been in debt for a long time and has low credit, which increases the risk of bad debt losses; it also means that the company is not effective in collecting accounts. The assets form bad debts, resulting in illiquid current assets, which are highly detrimental to the company's average production and operation. However, on the other hand, if the level of the company's accounts receivable turnover days is too low, it indicates that the company pursues a tight credit policy and the payment terms are too harsh, which will limit the expansion of the company's sales, especially when such restrictions on opportunity cost are more significant than the cost of credit sales; this will affect the company's profitability and thus its performance.

5.4.5.4 Concentration of ownership (TOP)

Ownership concentration significantly impacts corporate financial decision-making: higher concentration gives more substantial incentives to significant shareholders and greater power to supervise management at a lower cost. The concentration of ownership also helps to discipline managers and increase firm value. Effective monitoring may reduce management consolidation and lead managers to reduce leverage. Therefore, this paper selects the degree of ownership concentration as a control variable and uses the indicator of the ownership ratio held by the company's top 10 shareholders to represent this.

5.4.5.5 Market value (MK)

For the development of enterprises, data on market value are critical because they reflect the value of the enterprise. Market value is a concrete reflection of the investment value of a listed company and is equal to the wealth value of all shareholders of the listed company. Good value, in theory, will lead to a reasonable price; conversely, without good value, it is difficult to have a reasonable price. Even if a reasonable price appears, it will not be sustainable without the support of value. Generally speaking, the better a business performs, the higher its market value. The worse a company's performance is, the lower its market value will be. These two different situations will also affect the enterprise, leading to changes in corporate management and strategic decision-making. Therefore, this study chooses company market value as a control variable.

5.4.5.6 Company growth rate (GRO)

A standard operating company needs continuous growth, which is reflected in the financial indicators, that is, the growth of operating income. A company has different lifecycle growth stages, and the direction of decision-making is different, which in turn affects its R&D intensity. Operating income will change with the company's different development stages. Therefore, this paper uses the operating income growth rate as a variable to measure

company growth.

5.4.5.7 Asset/liability ratio (LEV)

The asset–debt ratio is calculated by dividing the company’s total liabilities by its total assets at the year's end, which can reflect the company’s capital structure. In addition, interest on debt is tax-deductible, and the more short-term debt a company has, the lower the cost of capital for a company. It can also play a leverage role in improving efficiency. However, if this indicator is too high, it will increase the company’s debt repayment pressure and financial risks, both of which will affect R&D investment and thus affect company performance. Therefore, this research also uses the asset-liability ratio as a control variable.

5.5 Model building

The study attempts to answer the question of whether AI focus has an impact on firm performance. The starting point of the analysis is economic theory, which predicts that innovation management, the integration of new technologies and the training of additional technical talents will increase additional costs for the company, so there is a negative and significant relationship between them. Therefore, this study shows that a company's focus on AI will affect the firm performance. On the other hand, dynamic capabilities theory (DCT) (Daneshvar Kahkhi and Palvia, 2016) also suggests that a firm’s high level of cooperation and useability will affect its competitiveness, thereby affecting its performance. In my research, in addition to the economic theory and Daneshvar Kahkhi and Palvia’s (2016) DCT, Mueller’s (1996) talent management theory (TMT) is also used. This paper also considers market-based and financial-based performance metrics. Since no single model combines the AI focus, R&D investment, R&D staff ratio, top manager education level and firm performance variables, different models must be specified based on theoretical and empirical results and meet statistical requirements.

I propose a panel model that directly links predetermined firm AI concerns and firm

characteristics to time- and cross-sectionally varying measures of stock returns and financial performance. Over time, I used Chinese A-share listed companies for the sample collection. Drawing on economic theory, Kahkhi and Palvia's (2016) DCT and Mueller's (1996) TMT, my stock market- and financial-based performance model provides a comprehensive overview from 2014 to 2021 of the AI focus of China's listed companies, including their focus on different levels of intelligence (i.e. mechanical AI, thinking AI and feeling AI), as well as R&D investment, R&D staff ratio, top manager education level and firm performance. In this respect, I follow Heracleous (2001), who motivated researchers to develop other approaches that could combine multiple and multi-directional factors affecting firm performance and avoided focusing on only one model in which elements are related to firm performance.

In this model, I am trying to discover the importance of the variables; that is to say, the main variables that affect the dependent variable need to be identified. In such cases, the best method to utilise is multivariate regression. Multiple regression methods come in different forms, all of which are related to how the independent variables are selected (Pindyck and Rubinfeld, 2001). The statistical data can be managed through panel data methods for my research. Panel data methods combine time series of cross-sectional observations. This approach allowed using many cross-sectional variables (N) obtained over time (T). In this case, the number of observations is N at different times and can be estimated by other models.

5.5.1 General modelling framework for analysing panel data

Panel data models are estimated with unbalanced data after controlling for firm characteristics. In the panel data for this study, the same cross-sectional units (such as firms' AI focus, investment in R&D, R&D staff ratio, top manager education level and firm performance) are surveyed over time. A fundamental advantage of a panel dataset over a cross-sectional dataset is that it allows researchers greater flexibility in modelling differences

in behaviour across entities. The general form is

$$Y_{it} = \beta_1 + \sum_{j=2}^K \beta_j X_{jit} + \sum_{p=1}^S \gamma_p Z_{pit} + \delta_i + \varepsilon_{it}$$

Where Y is the dependent variable, X is the explanatory variable that needs to be observed, and Z is the unobserved explanatory variable, which impacts the dependent variable in each period. K means there are K regressors, excluding the constant term. T represents duration, while j and p represent observed and unobserved variables. δ_i represents the estimation error of the panel model. The model is a classic regression model. If no unobserved explanatory variables exist, the entire model can be viewed as an ordinary linear model fitted by least squares. Therefore, the problem is all due to unobserved effects, which is what happens in most applications. The error term is assumed to be uncorrelated with the independent variable for all periods. Another hypothesis of random effects models is that unobserved variables are uncorrelated with the included variables, in which case they may be included in the error term. In contrast, in a fixed effects model, the unobserved effects will go into the fixed statement of the regression model. Here, the effects of unobserved variables can be controlled (Greene, 2010).

However, panel data include a wide variety of different models. This study uses three models, which are explained below. Of course, it must be noted that a multicollinearity test (variance inflation factor (VIF) test) must be performed before performing the following regression step analysis. The specific analysis will be shown in Chapter 6.

1. Pooled regression. If no unobserved variables exist, and Z in the above formula contains only constant terms, OLS is the best method for producing consistent and efficient estimators.

2. Fixed effects. If there is an unobserved variable Z and it is correlated with X, the least squares method will produce biased and inconsistent estimators. In this case, the following model will be considered:

$$Y_{it} = \beta_1 + \sum_{j=2}^K \beta_j X_{jit} + \alpha_i + \delta_t + \varepsilon_{it}$$

This formula captures all the observed effects and determines the mean value of the estimated conditions. FE models treat α_i as “a constant term in the regression model for a particular group.”

3. Random effects. If it is assumed that unobserved individual heterogeneity is not correlated with the included explanatory variables, the following model formula has to be considered:

$$Y_{it} = \beta_1 + \sum_{j=2}^K \beta_j X_{jit} + \alpha + u_i + \varepsilon_{it}$$

This formulation is a linear regression model with compound disturbances that can be estimated consistently but less efficiently by least squares. u_i in the formula represents the random elements of a particular group, similar to ε_{it} ; they differ in that, for each group, only one identical draw per epoch enters the regression.

The most important distinctions between FE and RE models are whether unobserved individual effects are relevant to whether regressors are present in the model and whether these effects are random or non-random (Greene, 2010).

5.5.2 Regression methodology and proposed model

1. Baseline equation. The study explores data using descriptive statistics as well as correlation analysis; however, the primary analysis method used is regression. The regression analysis aims to explore the relationship between AI focus quantitatively, the mediating effects of R&D investment and R&D staff ratio, the moderating role of EDU, and firm performance so that the relationships between the variables are quantitatively estimated. To study the impact of AI focus on firm performance, this study constructs regression model 1, based on Hypothesis 1, as follows:

$$Per_{it} = \beta_0 + \beta_1 AIF_{it} + \beta_i X_{it} + \varepsilon_{it} \quad (5 - 1)$$

In the above equation, it refers to the accounting indicator ROA and the market indicator Tobin's Q ratio, θ_0 is the constant item and AIF refers to the independent variables of this study. X_{it} refers to the control variable of this study, ε_{it} is a random error item, i refers to the company and t refers to time.

2. Mediating effect equation. In order to test the mediating effects of other variables, this study further constructs the following model 3 and model 4, based on Hypotheses 3.1, 3.2, 4.1 and 4.2 as follows:

$$Mediator_{it} = \theta_0 + \theta_1 AIF_{it} + \gamma_i X_{it} + \theta_t + \varepsilon_{it} \quad (5-2)$$

$$Per_{it} = \gamma_0 + \gamma_1 AIF_{it} + \gamma_2 Mediator_{it} + \gamma_i X_{it} + \theta_t + \varepsilon_{it} \quad (5-3)$$

where $Mediator_{it}$ refers to the mediating variables of this study, i.e. R&D investment and R&D staff ratio. If $\theta_1 \gamma_2 \gamma_1$ are all significant, it means that the addition of the mediating variables has changed the influence coefficient of AI focus on firm performance, indicating that there is a partial mediation. If $\theta_1 \gamma_2$ is significant and γ_1 is not significant, it means that the impact of AI focus on firm performance is fully affected through the mediating variables, and there is complete mediation. Per_{it} refers to the accounting indicator ROA and market indicator Tobin's Q. γ_0 is the constant item and AIF refers to the independent variables of this study; ε_{it} is a random error item, X_{it} refers to the control variables of this study, i refers to the company and t refers to time.

3. Moderating effect equation. In order to test the role of the moderating variable, regression model 2 is constructed based on Hypothesis 2 in this paper as follows:

$$Per_{it} = \alpha_0 + \alpha_1 AIF_{it} * Moderator_{it} + \alpha_2 AIF_{it} + \alpha_3 Moderator_{it} + \alpha_i X_{it} + \varepsilon_{it} \quad (5-4)$$

where Per_{it} refers to the accounting indicator ROA and market indicator Tobin's Q, α_0 is a constant item and AIF refers to the independent variables of this study. The moderator is top manager at the education level(EDU). ε_{it} is a random error item and X_{it} refers to the control variable. When the interaction term $a > 0$, it means that the larger the value of the moderating variable, the greater the promotion effect of AI focus on firm performance; when the interaction term $a < 0$, it means that the larger the value of the moderating variable, the smaller the promotion effect of AI focus on firm performance.

4. Lagging effect equation. In order to test the lag of the impact of corporate AI focus, R&D investment and R&D staff ratio on firm performance, regression model 5 is constructed as follows:

$$Per_{it-j} = \beta_0 + \beta_1 AIF_{it-j} + \beta_i X_{it-j} + \varepsilon_{it-j} \quad (5-5)$$

where j represents the lag period, $j=1, 2, 3$); Per_{it-j} refers to the lagging accounting indicator ROA and the market indicators TBQ; β_0 is the constant item; AIF_{it-j} refers to the lagging independent variables of this study; X_{it-j} refers to the control variable of this study; ε_{it-j} is a random error item; i refers to the company; and t and j refer to time.

5.6 Chapter summary

This chapter has discussed the research philosophy, design and methods of data analysis. The research methods chosen were deductive and quantitative data analysis methods, which were considered the most appropriate methods as the researcher collected data from two databases, CSMAR and Wind. The collected data were analysed using the statistical software STATA 17.0. This chapter has also described the research framework, operating model, and variable specification. In addition, the researcher elaborated on the different estimation techniques used in the study, including three econometric methods in panel regression estimation: OLS,

RE and FE.

Next, Chapter 6 provides the data analysis and results, Chapter 7 discusses the findings and Chapter 8 presents the conclusion of the paper, discussing the research limitations, implications, areas for further research and recommendations.

CHAPTER SIX: DATA ANALYSIS AND RESULTS

6.0 Introduction

Chapter 5 established the research concept of this study and explained the research methods, research empirical model, data collection and measurement of the variables. This chapter presents the statistical techniques used in the data analysis and the results of the empirical analysis. Sections 6.1 to 6.4 report the descriptive statistics, correlation analysis, multicollinearity, and Hausman tests. Section 6.5 presents the empirical results of the direct impact of AI focus on the performance of Chinese listed companies. The mediating effects of R&D investment and the R&D staff ratio on the relationship between AI focus and firm performance and the moderating effect of top manager education level on the relationship between AI focus and firm performance are discussed in Sections 6.6 and 6.7, respectively. The results of the robustness checks are provided in Section 6.8, Section 6.9 analyses the impact of different components of AI, focusing on firm performance, and Section 6.10 provides a chapter summary.

6.1 Descriptive statistics

Table 6.1 summarises the descriptive statistics and provides an overview of the variables used in the research model. It shows the nature of all the variables considering the following statistical distributions: mean, standard deviation, minimum, and maximum values of the dependent and control variables.

Table 6.1 Descriptive statistics

VarName	Obs	Mean	SD	Median	Min	Max
ROA	20474	0.037	0.080	0.042	-0.363	0.238
TQ	20474	2.310	1.694	1.770	0.837	11.672
AI	20474	0.064	0.136	0.020	0.000	1.115
RDD	20474	10.973	12.701	8.400	0.000	63.950
RDI	17177	18.116	1.640	18.155	5.094	22.182
EDU	20474	7.372	5.712	7.000	0.000	25.000
SIZE	20474	22.629	1.454	22.416	19.735	27.683
TOP	20474	0.144	0.109	0.110	0.014	0.525
ATO	20474	0.584	0.434	0.489	0.025	2.564
REC	20474	33.960	121.565	5.575	0.120	986.906
MV	20474	23.201	1.221	22.969	21.164	27.697
GRO	20474	0.157	0.481	0.081	-0.629	3.235
LEV	20474	0.465	0.214	0.458	0.064	0.963

Notes: This table shows the statistical data of China's listed companies from 2014 to 2022. It includes 20,474 firm-year observations among companies listed on the Shanghai or Shenzhen stock exchanges.

Table 6.1 reports the descriptive statistical results of the main variables. The mean value of the indicator measuring corporate financial performance (ROA) is 0.037 and the standard deviation is 0.080. The standard deviation is larger than the mean, indicating that the overall total asset profit rate fluctuates greatly. The average value of the enterprise's Tobin's Q value (TQ) is 2.310, the maximum value is 11.672, the minimum value is 0.837 and the standard deviation is 1.694. The difference between the minimum and maximum values is significant, indicating that the market performance development level of the sample enterprises is very different. The average value of the enterprise AI focus is 0.064, which is higher than previous research. For example, Mishra *et al.*'s study conducted descriptive statistical analysis on AI in different industries, and they believe that there are significant differences among different industries. For example, the average AI value for commercial equipment is the highest (0.019%), while the average AI value for utilities is the lowest (0.009%) (Mishra *et al.*, 2022). And the average AI value in this research is higher. The standard deviation is 0.136, the minimum value is 0.000 and the maximum value is 1.115. The standard deviation is greater

than the mean, indicating a significant difference in the AI focus of the sample companies. The difference between the minimum and maximum values is substantial, indicating that different companies have different levels of AI focus. The average R&D staff ratio (RDD) is 10.973, with a standard deviation of 12.701. The large standard deviation indicates a significant difference in the R&D staff ratio among different enterprises. The average R&D investment (RDI) is 18.116, with a standard deviation of 1.640. The smaller standard deviation ratio indicates that the differences in R&D investment between firms are not significant. Top managers' average highest education level (EDU) is 7.372, with a standard deviation of 5.712. The difference in highest education levels among executives in the sample companies is not significant. However, the minimum value of AI is 0, and there are a total of 6841 observations in the sample that are 0. The minimum value of RDD is 0, and there are a total of 7969 observations in the sample that are 0. The minimum value of EDU is 0, and there are a total of 2487 observations in the sample with a value of 0. Based on the total sample observation value of 20474.

The average company asset size (SIZE) is 22.629, with a standard deviation of 1.454. The small standard deviation indicates that the asset size of the sample companies does not differ significantly. The average concentration of ownership (TOP) is 0.144, with a standard deviation of 0.109. The average accounts receivable turnover ratio (ATO) is 0.584, with a standard deviation of 0.434. The sample companies' "total liabilities/total assets" is high, but the difference is not significant. The average accounts receivable turnover ratio (REC) is 33.960, with a standard deviation of 121.565. The standard deviation is greater than the mean, indicating a significant difference in the accounts receivable turnover ratio of the sample companies. The average market value (MV) value is 23.201, with a standard deviation of 1.221. This indicates that the sample companies' net cash flow/total assets' is high, but the difference is not significant. The average growth rate (GRO) is 0.157, with a standard deviation of 0.484. The standard deviation is greater than the mean, indicating a significant difference in the growth rate of the sample companies. The average asset/liability ratio (LEV)

is 0.465, with a standard deviation of 0.214. The sample companies' total liabilities/total assets are not high, but the difference is significant.

6.2 Correlation analysis

Correlation analysis refers to the analysis of two or more correlated variable elements to measure the close correlation between the two variable factors. There needs to be a certain connection or probability between the correlation elements before correlation analysis can be performed.

This thesis chooses the correlation coefficient for correlation analysis. The correlation coefficient is a quantity that measures the degree of linear correlation between research variables. When the correlation coefficient is greater than 0, there is a positive correlation between the two variables; when the correlation coefficient is less than 0, there is a negative correlation between the two variables; and when the correlation coefficient is equal to 0, it means that there is no linear relationship between the two variables.

This section introduces the results of the univariate correlation analysis of the relationship between AI focus, R&D investment, R&D staff ratio, top manager education level and firm performance. Pearson's coefficient is used to test the correlation of each variable in Equation 5-1 described in Chapter 5. The test results are shown in *Table 6.2*. There is a negative correlation between enterprise market performance (TQ) and AI focus; the correlation coefficient between corporate ROA and AI focus (AI) is -0.05, which is significantly negative at the 1% level. The correlation analysis results preliminarily support **H1a,b**. However, regression analysis will be used to explore the hypothesis further because the above observation results do not consider the role of heterogeneous characteristics such as individual companies, time and other factors that may affect the relationship between the two.

The coefficients of the highest education level of top managers (EDU) and firm performance (ROA and TQ) are -0.02 and -0.09, respectively, indicating a negative correlation; the company ROA and Tobin's Q ratio are significant at the 1% level. The correlation analysis

results preliminarily support **H2a,b**. The coefficients of R&D investment (RDI) and firm performance (ROA and TQ) are 0.13 and -0.19, respectively, indicating that they are significantly correlated; the company ROA and Tobin's Q ratio are significant at the 1% level. The correlation analysis results provide support for **H3**. The coefficients for the R&D staff ratio (RDD) and firm performance (ROA and TQ) are -0.07 and 0.13, respectively, indicating that they are significantly correlated; the company ROA and Tobin's Q ratio are significant at the 1% level. The correlation analysis results provide support for **H4**.

Table 6. 2 Pearson correlation test

	ROA	TQ	AI	RDD	RDI	EDU	SIZE	TOP	ATO	REC	MV	Growth	LEV
ROA	1												
TQ	0.05***	1											
AI	-0.05***	-0.00	1										
RDD	-0.07***	0.13***	0.32***	1									
RDI	0.13***	-0.19***	0.15***	0.27***	1								
EDU	-0.02***	-0.09***	0.07***	0.07***	0.20***	1							
SIZE	0.12***	-0.47***	-0.06***	-0.16***	0.53***	0.32***	1						
TOP	0.16***	-0.12***	-0.11***	-0.19***	0.08***	0.04***	0.29***	1					
ATO	0.15***	-0.02***	-0.03***	-0.06***	0.17***	-0.07***	-0.02***	0.06***	1				
REC	0.08***	-0.01	-0.08***	-0.14***	-0.01	-0.02**	0.07***	0.07***	0.12***	1			
MV	0.18***	-0.18***	-0.06***	-0.11***	0.53***	0.33***	0.94***	0.29***	-0.02***	0.08***	1		
GRO	0.22***	0.07***	0.00	0.00	0.04***	0.01*	0.03***	0.02***	0.07***	0.02***	0.05***	1	
LEV	-0.27***	-0.25***	-0.09***	-0.21***	0.13***	0.13***	0.46***	0.07***	0.07***	0.05***	0.41***	0.00	1

Notes: Asterisks *, **, *** indicate that correlation is significant at 0.1, 0.05, and 0.01 levels (two-tailed, Pearson). See Table 5.7 for the definition of variables.

Table 6.2 reports the pairwise correlations between the variables used in Equation 5-1 described in Chapter 5. As mentioned in Chapter 5, a dynamic fixed effects model was used to test the research hypotheses, while data with variables lagged by one period were used as a robustness check.

Therefore, it is essential to test for multicollinearity, autocorrelation and homoskedasticity. First, multicollinearity among the independent variables was tested by performing a

correlation matrix analysis. *Table 6.2* provides pairwise correlations between all the independent variables used in this paper. The purpose of reporting correlation estimates is to check for multicollinearity problems in regression analyses.

6.3 Multicollinearity test

Multicollinearity refers to the fact that there is a precise correlation or a high degree of correlation between the explanatory variables in the linear regression model, which makes the model estimation distorted or difficult to estimate accurately. The variance inflation factor (VIF) measures the severity of complex (multi)collinearity in a multiple linear regression model. It represents the ratio of the variance of the regression coefficient estimator compared to the variance if the independent variables are assumed to be nonlinearly related. The larger the VIF coefficient, the greater the possibility of collinearity between independent variables. Generally speaking, if the variance inflation factor exceeds 10, the regression model has severe multicollinearity.

In addition, *Table 6.3* shows the results of the multicollinearity test for the variable in the 5-1 model. The tolerance statistics described by the VIF confirm that the maximum value of VIF here is 8.69, and the mean value is 2.92, which is less than the empirical critical value of 10. Thus, the above model settings do not exhibit severe multicollinearity.

Table 6.3 Multicollinearity test results

Variable	VIF	1/VIF
SIZE	8.69	0.115065
MV	8.15	0.122638
LEV	1.31	0.763662
TOP	1.12	0.892629
ATO	1.03	0.966660
REC	1.03	0.972703
AI	1.02	0.976065
GRO	1.01	0.988660
Mean VIF	2.92	

Note: VIF statistics are from the statistical estimations depicted in Table 6.3

6.4 F-test and Hausman test

As discussed above, there are three types of regression models for panel data, namely, OLS, RE and FE. The F-test is used to determine whether to choose FE or OLS. When the P value of the test is more significant than 0.1, the null hypothesis is accepted, and the OLS model is selected; when the P value of the test is less than 0.1, the null hypothesis is rejected, and the FE model is selected. When the P value of the test is less than 0.1, the null hypothesis is rejected, and the RE model is selected. The Hausman test is used to determine whether to choose FE or RE. When the P value of the test is more significant than 0.1, the null hypothesis is accepted, and the RE model is selected; when the P value of the test is less than 0.1, the null hypothesis is rejected, and the FE model is selected.

The test results, including the Hausman test results, are shown in *Table 6.4*. The Hausman test statistics for model 1 and model 2 are 295.84 and 290.86, respectively. The P value is rejected at the significance level of 0.01, and the null hypothesis is rejected. The RE model is better than the FE model; the model can be set as an FE model; the F statistics of model 1 and model 2 are 3.77 and 6.81, respectively. The P value is rejected at the significance level of 0.01, and the FE model is better than the null hypothesis. In summary, the FE model was finally selected.

Table 6.4 F-test and Hausman test results

Model Number (Dependent Variable)	Test Name	Chi Sq. Statistic	Prob.	Test Results
Model 1 (TQ)	F-Test	3.76	0.0000	Select fixed effects
	Hausman Test	288.64	0.0000	Select fixed effects
Model 2 (ROA)	F-test	6.78	0.0000	Select fixed effects
	Hausman Test	280.59	0.0000	Select fixed effects

6.5 Regression results between AI focus and firm performance

To test the hypotheses, the study employed three econometric methods for panel regression estimation: OLS, RE and FE. The FE and RE outputs were reported for comparison, although the F-test and Hausman test favour FE.

On the one hand, Column (3) of *Table 6.5.1* analyses the impact of AI focus on enterprise market performance. The regression coefficient of AI focus is -0.313, which is less than 0, and the P value is less than 0.01, indicating that at the 1% significance level, enterprises focus highly on AI technology. This will cause enterprises to face difficulties such as a shortage of operating funds, significantly inhibiting their market performance. **H1b** has thus been verified.

Moreover, regarding AI focus in all three models (OLS, FE and RE), the AI focus coefficient is negative, suggesting that increased AI focus is linked to a lower Tobin's Q ratio. In both the OLS and FE models, this finding is statistically significant at the level of 0.1. Accordingly, several points can be noted. Firstly, based on the topic of AI focus and firm performance, due to the negative correlation between AI focus and Tobin's Q ratio, it is anticipated that organisations with a higher AI focus will also have a lower Tobin's Q ratio, which will indicate poor overall firm performance. This could be due to the negative effects that

adopting AI has on several firm performance metrics, including efficiency, productivity and innovation. Secondly, firm size (SIZE) negatively impacts Tobin's Q ratio in the context of AI focus and firm performance because there is an association between Tobin's Q ratio and firm asset size. Firm size can still influence certain aspects of firm performance, which is taken into consideration by Tobin's Q ratio. Thirdly, given the context of AI focus and firm performance, concentration of ownership (TOP) and accounts receivable turnover ratio (REC) does not significantly affect the Tobin's Q ratio. This is supported by the lack of a strong association between the concentration of ownership, accounts receivable turnover ratio (REC) and Tobin's Q ratio. Other factors may have a more significant impact on a firm's performance. Fourthly, given the significant positive correlation between the growth rate (GRO) and the Tobin Q ratio, it is expected that companies with reasonable growth rates will generally perform better. This may be due to the potential for higher profitability of the enterprise. Fifthly, companies with higher market value (MV) usually have higher Tobin Q ratio values, indicating that, based on the correlation of high market value, companies will have more competitiveness to provide development for the company, thereby improving the company's market performance.

Table 6.5.1 Regression results for Tobin's Q ratio and AI focus

	(1) OLS	(2) RE	(3) FE
	TQ	TQ	TQ
AI	-0.304*** (-6.585)	-0.201*** (-4.317)	-0.313*** (-3.992)
SIZE	-2.898*** (-51.125)	-2.821*** (-48.537)	-2.875*** (-33.299)
TOP	-0.243*** (-3.312)	-0.271*** (-2.905)	0.186 (1.061)
ATO	-0.137*** (-5.056)	-0.151*** (-4.187)	-0.184*** (-3.180)
REC	0.000 (1.346)	0.000 (0.162)	0.000 (0.102)
MV	2.968*** (48.448)	2.939*** (41.990)	3.030*** (29.763)
GRO	0.120*** (5.955)	0.065*** (3.822)	0.063*** (3.674)
LEV	0.218** (2.477)	-0.067 (-0.823)	-0.220** (-2.127)
_cons	-0.958*** (-3.014)	-1.875*** (-4.156)	-2.722*** (-3.326)
N	20474	20474	20472
Adjusted R2	0.797	0.795	0.880
F/Wald statistic (p-value)	700.654*** (0.000)	3964.98*** (0.000)	162.660*** (0.000)
Hausm (p-value)			280.59*** (0.000)

Notes: The *t* values in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

On the other hand, Column (3) of *Table 6.5.2* analyses the impact of AI focus on corporate financial performance. The regression coefficient of AI focus is -0.020, less than 0, and the P value is less than 0.01, indicating that at the 1% significance level, a high focus of corporate AI will significantly inhibit the corporate financial performance. Hypothesis **H1a** has been verified. This may be because the development of AI technology requires a significant investment, and technological innovation activities generally have an extended return cycle.

For example, companies need a considerable amount of money and time to train talents suitable for applications related to AI technology. Therefore, in the early stages of the application of AI equipment, companies are still unable to obtain considerable returns based on it, thus reducing the profit created by unit assets, that is, the total asset profit rate.

Table 6.5.2 Regression results for ROA and AI focus

	(1) OLS ROA	(2) RE ROA	(3) FE ROA
AI	-0.027*** (-6.068)	-0.032*** (-7.165)	-0.020*** (-2.633)
SIZE	-0.003** (-1.990)	-0.004** (-2.360)	0.006* (1.918)
TOP	0.058*** (8.074)	0.070*** (8.929)	0.056*** (3.711)
ATO	0.029*** (13.959)	0.033*** (13.315)	0.042*** (9.188)
REC	0.000*** (4.282)	0.000*** (2.920)	0.000 (0.140)
MV	0.024*** (12.564)	0.026*** (15.084)	0.029*** (11.504)
GRO	0.031*** (23.579)	0.031*** (25.328)	0.028*** (22.218)
LEV	-0.153*** (-31.022)	-0.182*** (-33.652)	-0.225*** (-29.266)
_cons	-0.399*** (-23.488)	-0.438*** (-25.156)	-0.704*** (-15.968)
N	20474	20474	20472
Adjusted R2	0.248	0.246	0.438
F/Wald statistic (p-value)	224.181*** (0.000)	2013.42*** (0.000)	199.767*** (0.000)
Hausm (p-value)			288.64*** (0.000)

*Notes: The t values are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Furthermore, considering AI focus and firm performance, the following points can be noted along with the potential mediators and moderating variables. Firstly, a positive correlation

exists between company asset size (SIZE) and financial performance (ROA), which is significant at the 10% level. Since a positive correlation exists between company asset size (SIZE) and ROA, companies with more considerable company assets are likely to see a higher ROA. This may be due to the growing impact of asset size on returns, especially during periods of economic expansion. Secondly, concentration of ownership (TOP) is positively related to financial performance (ROA), which is significant at the 1% level. The results show that ownership concentration significantly affects ROA in the context of AI focus and firm performance. Moreover, the total asset turnover ratio (ATO) and market value (MV) are also positively related to financial performance (ROA) and are significant at the 1% level. This suggests that differences in ROA can be significantly explained by the total asset turnover ratio and market value in the context of AI focus and firm performance. Thirdly, there is no significant correlation between the accounts receivable turnover ratio (REC) and ROA, suggesting that the accounts receivable turnover ratio does not impact company ROA in the context of AI focus and firm performance. Fourthly, there is a significant positive correlation between growth rate (GRO) and ROA, which proves that the better the company's product sales, the higher the company's rate of return, which in turn affects the company's financial performance. Fifthly, regarding the asset-liability ratio (LEV), there is a significant negative correlation between the asset/liability ratio and financial performance (ROA), indicating that the lower the company's asset/liability ratio, the better the company's financial status, thereby improving firm performance.

6.6 Robustness checks

Robustness testing examines the robustness of the evaluation methods and indicators' explanation ability; that is, when specific parameters are changed, whether the evaluation methods and indicators still maintain a relatively consistent and stable explanation of the evaluation results. In layman's terms, this means changing a specific parameter and conducting repeated experiments to observe whether the empirical results change with the change in parameter settings. If, after changing the parameter settings, it is found that the sign

and significance have changed, the explanation is not robust, and this requires finding the problem.

This section adopts the following two methods to conduct robustness testing.

6.6.1. Lagging the research variables by one period

Academics often use the method of lagging the research variables by one period to explore the relationship between corporate innovation and company performance. In this section, the study will lag the explanatory variables by one period to examine the impact of the research method selection on the research results. The results reported in *Table 6.6.1* show that the coefficients of the AI variables are -0.024 and -0.289, which are less than 0, and both pass the 5% level significance test, indicating the conclusion of this study: a high degree of AI focus in enterprises will significantly inhibit enterprises' solid firm performance.

Table 6.6.1 Robustness check of one lagged study variable

	(1) ROA	(2) TQ
L.AI	-0.024** (-2.539)	-0.289*** (-3.157)
SIZE	0.011*** (3.279)	-2.879*** (-30.588)
TOP	0.050*** (2.842)	0.387* (1.744)
ATO	0.042*** (7.997)	-0.183*** (-2.943)
REC	0.000 (0.035)	-0.000 (-0.045)
MV	0.030*** (10.448)	3.025*** (26.497)
Growth	0.027*** (20.700)	0.061*** (3.202)
LEV	-0.243*** (-27.696)	-0.335*** (-2.943)
_cons	-0.824*** (-15.412)	-2.494** (-2.573)
N	17962	17962
Adjusted R2	0.445	0.888
F	178.351*** (0.000)	144.409*** (0.000)

*Notes: The t values are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

6.6.2. Replacing the explained variable

This section replaces ROA with ROA1 and TQ with TobinQA to conduct a robustness test. The results, reported in *Table 6.6.2*, show that the coefficients of the AI variables are -0.016 and -0.172, which are less than 0. Both pass the 5% level significance test, indicating the conclusion of this study: a high degree of enterprise AI focus will significantly inhibit enterprises' solid financial performance.

Table 6.6.2 Robustness check by replacing the explained variable

	(1) ROA1	(2) TobinQA
AI	-0.016** (-2.230)	-0.172*** (-3.162)
SIZE	0.008*** (2.810)	-2.681*** (-35.401)
TOP	0.055*** (3.815)	0.240* (1.786)
ATO	0.033*** (7.853)	-0.015 (-0.388)
REC	0.000 (0.285)	0.000 (0.851)
MV	0.027*** (11.341)	2.729*** (30.060)
Growth	0.027*** (22.658)	-0.008 (-0.618)
LEV	-0.247*** (-33.189)	-0.026 (-0.317)
_cons	-0.706*** (-16.821)	-0.575 (-0.843)
N	20472	20472
Adjusted R2	0.452	0.901
F	225.387*** (0.000)	206.768*** (0.000)

*Notes: The t values in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

6.7 Endogeneity test with 2SLS models

Endogeneity refers to the fact that one or more explanatory variables in the model are related to random disturbance terms. The main reasons leading to the existence of endogeneity are as follows:

1. Omitted variables and the omitted variables are related to other variables introduced into the model.
2. The explanatory variables and the explained variables interact, influence each other and

demonstrate cause and effect.

3. Self-selection bias.

4. Sample selection bias.

This thesis uses the instrumental variable method to solve the endogeneity problem. It uses the average AI value of other companies in the company's industry in the same year as the instrumental variable. *Table 6.7* shows the results. It can be seen that the t value of the instrumental variable is significant at the 1% significance level, and the F value in the first stage is greater than 10, indicating that the instrumental variable is an effective instrumental variable. At this time, the coefficients of AI are -0.202 and -3.309, respectively, and the P values are both less than 0.01, indicating that after considering endogeneity issues, a high degree of corporate AI focus will still significantly inhibit firm performance.

Table 6.7 Endogeneity test using 2SLS

	(1)2SLS ROA	(2)SLS TQ
AI	-0.202*** (-3.717)	-3.309*** (-4.914)
SIZE	0.007** (2.411)	-2.844*** (-32.583)
TOP	0.052*** (3.382)	0.128 (0.705)
ATO	0.043*** (9.177)	-0.165*** (-2.812)
REC	0.000 (0.099)	0.000 (0.053)
MV	0.029*** (11.458)	3.023*** (29.594)
Growth	0.028*** (21.649)	0.056*** (3.191)
LEV	-0.223*** (-28.593)	-0.210** (-1.996)
N	20430	20430
Adjusted R2	0.186	0.634
F	193.338	159.040
Instrumental variable t value	12.22***(0.000)	12.22***(0.000)
First stage F value	149.45	149.45

Notes: The t values in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

6.8 Moderating effect of top manager education level between AI focus and firm performance

In this section, the research uses a university degree or above as a stratification indicator for top manager education level. *Table 6.8* shows the empirical results of the moderating effect of top manager education level on the relationship between AI focus and firm performance. The regression coefficients of the cross-term AI*EDU are 0.002 and 0.018, respectively, both of which are greater than 0 and significant at the 10% significance level, indicating that

executive education level can moderate the relationship between AI focus and firm performance. The coefficient is greater than 0, indicating that when the level of executive education increases, the negative relationship between AI focus and firm performance will be weakened, and hypothesis **H2a,b** has been verified.

Table 6.8 Moderating effect model for EDU

	(1) ROA	(2) TQ
AI	-0.022*** (-2.840)	-0.333*** (-4.233)
AI_EDU	0.002** (2.027)	0.018* (1.816)
EDU	-0.001*** (-4.148)	-0.001 (-0.564)
SIZE	0.006** (2.178)	-2.874*** (-33.270)
TOP	0.057*** (3.819)	0.193 (1.097)
ATO	0.042*** (9.290)	-0.183*** (-3.162)
REC	0.000 (0.107)	0.000 (0.092)
MV	0.030*** (11.530)	3.030*** (29.765)
Growth	0.028*** (22.163)	0.063*** (3.683)
LEV	-0.225*** (-29.334)	-0.222** (-2.145)
_cons	-0.716*** (-16.338)	-2.747*** (-3.354)
N	20472	20472
Adjusted R2	0.438	0.880
F	162.616	130.395

*Notes : The t values in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

6.9 Mediating effect of R&D investment between AI focus and firm performance

Drawing on the research methods of Baron and Kenny (1986) and Wen and Ye (2014), the stepwise regression coefficient method was first used to test the mediating effect of R&D investment (see *Table 6.9*). The regression results of model (1) in *Table 6.9* show that AI focus can significantly reduce corporate financial performance; the regression results of model (4) show that AI focus can substantially reduce corporate market performance.

The following regression results of model (2) and model (5) show that the coefficient of AI focus is 0.353, which is greater than 0, and the P value is less than 0.01, indicating that AI focus significantly increases RDI. The research results support hypothesis **H3.1**.

In addition, model (3) adds RDI to the control variables based on the settings of model (1), while model (6) adds RDI to the control variables based on the settings of model (4). Therefore, the results of model (3) and model (6) show that the coefficient of AI focus is still significantly negative at the 5% significance level. Currently, the regression coefficients of R&D investment are -0.004 and -0.028, respectively, both significant at the 10% level; the research results, therefore, support hypothesis **H3.2a,b**.

After adding the RDI variable to models (1) and (4), the absolute values of the regression coefficients of AI focus in models (3) and (6) both are negative and significant, indicating that RDI plays an essential role in corporate AI focus and firm performance. There is a partial mediating effect between them, that is, a high degree of AI focus will increase RDI, thereby reducing corporate financial performance and market performance. Hypothesis **H3** is verified.

Table 6.9 Mediating effect model for RDI

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	RDI	ROA	TQ	RDI	TQ
AI	-0.020*** (-2.633)	0.353*** (4.801)	-0.019** (-2.403)	-0.313*** (-3.992)	0.353*** (4.801)	-0.345*** (-4.236)
SIZE	0.006* (1.918)	0.789*** (20.448)	0.007** (1.995)	-2.875*** (-33.299)	0.789*** (20.448)	-2.802*** (-32.170)
TOP	0.056*** (3.711)	0.268 (0.979)	0.062*** (3.542)	0.186 (1.061)	0.268 (0.979)	0.036 (0.202)
ATO	0.042*** (9.188)	0.577*** (10.712)	0.046*** (8.015)	-0.184*** (-3.180)	0.577*** (10.712)	-0.191*** (-3.709)
REC	0.000 (0.140)	-0.000 (-0.117)	0.000 (0.189)	0.000 (0.102)	-0.000 (-0.117)	0.000 (0.577)
MV	0.029*** (11.504)	0.075** (2.553)	0.034*** (11.979)	3.030*** (29.763)	0.075** (2.553)	3.013*** (27.128)
Growth	0.028*** (22.218)	-0.037** (-2.370)	0.033*** (21.143)	0.063*** (3.674)	-0.037** (-2.370)	0.075*** (4.004)
LEV	-0.225*** (-29.266)	-0.488*** (-5.833)	-0.238*** (-28.072)	-0.220** (-2.127)	-0.488*** (-5.833)	-0.226** (-2.438)
RDI			-0.004*** (-3.120)			-0.028* (-1.769)
_cons	-0.704*** (-15.968)	-1.596** (-2.215)	-0.764*** (-14.562)	-2.722*** (-3.326)	-1.596** (-2.215)	-3.487*** (-3.876)
N	20472	17126	17126	20472	17126	17126
Adjusted R2	0.438	0.882	0.453	0.880	0.882	0.884
F	199.767	119.710	170.891	162.660	119.710	170.640

Notes : The *t* values in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.10 Mediating effect of R&D staff ratio between AI focus and firm performance

Table 6.10 shows the results of the mediating effect of the R&D staff ratio. The regression results of model (1) in Table 6.10 show that AI focus can significantly reduce corporate financial performance; the regression results of model (4) show that AI focus can substantially reduce corporate market performance.

The regression results of model (2) and model (5) show that the coefficient of AI focus is 13.746, which is greater than 0, and the P value is less than 0.01, indicating that AI focus has significantly increased the R&D staff ratio in the enterprise. The research results support hypothesis **H4.1**. This is because the AI development of intelligence is highly dependent on technology, requiring many R&D staff to support enterprises in developing AI and giving full play to its scale advantages.

In addition, model (3) adds the R&D staff ratio (RDD) to the control variables based on the settings of model (1). In contrast, model (6) adds the R&D staff ratio (RDD) to the control variables based on the settings of model (4). Therefore, the results of models (3) and (6) show that the coefficient of enterprise AI focus is still significantly negative at the 5% significance level. Currently, the regression coefficients of the R&D staff ratio are, respectively, -0.001 and -0.002; both are less than 0, and the P values are both significant at the 5% significance level. The research results support hypothesis **H4.2a,b**.

After adding the RDD variable to models (1) and (4), the absolute values of the regression coefficients for AI focus in models (3) and (6) both are negative and significant, indicating that the R&D staff ratio plays a vital role in AI focus. There is a partial mediating effect between AI focus and firm performance; that is, a high degree of AI focus will increase the R&D staff ratio in the company, thereby reducing the company's financial performance and market performance. Therefore, hypothesis **H4** has been verified.

Table 6.10 Mediating effect model for RDD

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	RDD	ROA	TQ	RDD	TQ
AI	-0.020*** (-2.633)	13.746*** (10.889)	-0.015** (-2.020)	-0.313*** (-3.992)	13.746*** (10.889)	-0.288*** (-4.078)
SIZE	0.006* (1.918)	0.863*** (2.622)	0.006** (2.016)	-2.875*** (-33.299)	0.863*** (2.622)	-2.874*** (-169.963)
TOP	0.056*** (3.711)	-5.509*** (-2.745)	0.054*** (3.583)	0.186 (1.061)	-5.509*** (-2.745)	0.176 (1.641)
ATO	0.042*** (9.188)	0.004 (0.012)	0.042*** (9.183)	-0.184*** (-3.180)	0.004 (0.012)	-0.184*** (-8.229)
REC	0.000 (0.140)	0.001 (1.504)	0.000 (0.181)	0.000 (0.102)	0.001 (1.504)	0.000 (0.209)
MV	0.029*** (11.504)	0.258 (1.012)	0.030*** (11.495)	3.030*** (29.763)	0.258 (1.012)	3.030*** (181.855)
Growth	0.028*** (22.218)	-0.104 (-0.907)	0.028*** (22.184)	0.063*** (3.674)	-0.104 (-0.907)	0.063*** (6.607)
LEV	-0.225*** (-29.266)	-1.109 (-1.524)	-0.225*** (-29.377)	-0.220** (-2.127)	-1.109 (-1.524)	-0.222*** (-5.245)
RDD			-0.001*** (-3.281)			-0.002** (-2.502)
_cons	-0.704*** (-15.968)	-14.122** (-2.370)	-0.709*** (-16.067)	-2.722*** (-3.326)	-14.122** (-2.370)	-2.747*** (-9.892)
N	20472	20472	20472	20472	20472	20472
Adjusted R2	0.438	0.777	0.438	0.880	0.777	0.880
F	199.767	18.996	178.635	162.660	18.996	4064.453

Notes: The *t* values are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.11 Further analysis of the impact of different components of AI focus on firm performance

In this study, the AI focus rating comprises three-dimensional one-way scores according to certain weights. In order to further analyse the specific impact of AI focus on firm performance, according to the benchmark model, the AI component indicators and firm performance were regressed separately. The results are shown in *Table 6.11*. The results

show that the impact of the three component indicators on firm performance is significantly negative at the 5% level, among which feeling AI (FAFR) has the greatest impact on firm performance, followed by thinking AI (TAFR) and finally mechanical AI (MAFR).

This finding may be because AI technology is still in the developmental stage, especially high-intelligence technology (feeling AI). Companies need significant staff and material resources to develop and utilise this technology, unlike low-intelligence technologies (mechanical AI), which have already played a role in people's lives. Those in use are relatively mature. Therefore, at present, the higher the level of intelligence technology, the less likely it is to bring ideal benefits to firm performance.

Table 6.11 The impact of different components of AI on firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROA	ROA	TQ	TQ	TQ
MAFR	-0.016** (-2.028)			-0.329*** (-3.812)		
TAFR		-0.146*** (-3.110)			-1.188** (-2.427)	
FAFR			-0.694*** (-2.658)			-6.687*** (-2.853)
SIZE	0.005* (1.887)	0.006** (1.988)	0.006* (1.899)	-2.876*** (-33.316)	-2.875*** (-33.304)	-2.877*** (-33.331)
TOP	0.056*** (3.731)	0.054*** (3.626)	0.056*** (3.715)	0.191 (1.085)	0.179 (1.014)	0.189 (1.074)
ATO	0.042*** (9.186)	0.042*** (9.175)	0.042*** (9.186)	-0.184*** (-3.182)	-0.185*** (-3.203)	-0.185*** (-3.203)
REC	0.000 (0.144)	0.000 (0.118)	0.000 (0.134)	0.000 (0.108)	0.000 (0.091)	0.000 (0.100)
MV	0.029*** (11.507)	0.029*** (11.472)	0.029*** (11.481)	3.030*** (29.764)	3.029*** (29.756)	3.029*** (29.760)
Growth	0.028*** (22.233)	0.028*** (22.152)	0.028*** (22.171)	0.063*** (3.686)	0.063*** (3.676)	0.063*** (3.688)
LEV	-0.225*** (-29.264)	-0.225*** (-29.286)	-0.225*** (-29.305)	-0.219** (-2.123)	-0.221** (-2.143)	-0.221** (-2.144)
_cons	-0.703*** (-15.947)	-0.706*** (-16.021)	-0.702*** (-15.959)	-2.710*** (-3.312)	-2.717*** (-3.327)	-2.688*** (-3.287)
N	20472	20472	20472	20472	20472	20472
Adjusted R2	0.437	0.438	0.438	0.880	0.880	0.880
F	199.646	198.902	200.136	161.635	157.103	159.994

Notes : The *t* values in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.12 Chapter Summary

This chapter has presented and discussed the empirical results of the research hypotheses regarding the relationship between AI focus, R&D, top manager education level and firm performance, as discussed in the conceptual framework chapter (Chapter Four). Hypothesis 1

(see Section 6.5 and Section 6.7) examines the direct impact of AI focus on firm performance. Hypothesis 2 (see Section 6.8) discusses the moderating effect of top manager education level on the relationship between AI focus and firm performance. Hypotheses 3 and 4 (see Section 6.9 and Section 6.10) examine the mediating role of R&D in the relationship between AI focus and firm performance. Finally, Section 6.11 further analysed the impact of different components of AI focus on firm performance.

In summary, the results discussed in this chapter support several of the hypotheses. First of all, the research results of this chapter show that AI focus has a significant negative correlation with firm performance. In contrast, the impact of different components of AI focus on Tobin's Q and ROA is uneven. Among them, feeling AI has the most significant impact on company performance, followed by thinking AI and mechanical AI. Secondly, the R&D staff ratio and R&D investment play a partial intermediary role in the relationship between AI focus and firm performance. Finally, the education level of top managers has a moderating effect on the relationship between AI focus and firm performance.

CHAPTER SEVEN: DISCUSSION

7.0 Introduction

This chapter discusses the findings set out in the previous sections. The results, although assumed to support what has been done by AI-focused companies, are not in line with expectations. The following discussion has been conducted according to the economy theory, capability theory, and talent management theory, which shows the violation of cost management principles of enterprises with inefficient planning and risk estimation regarding business resources. This has led to the poor design of AI-related strategies, leading to a series of problems for firm performance. Overall, the research results have shown that a high level of AI in businesses often leads to challenges such as operational funding shortages, significantly restraining firm performance. Moreover, the results indicate that the R&D staff ratio serves as a mediator between AI focus and firm performance, but the function is quite limited or partial. Specifically, a higher level of AI focus is correlated with an increased presence of technical personnel in the company, resulting in a decline in financial performance. In addition, the research results show that R&D investment partially mediates, meaning that R&D acts as a mediator in the relationship between AI focus and firm performance. Finally, when the educational level of top managers increases, the negative correlation between AI focus and market performance for businesses diminishes. Based on these findings, this chapter aims to discuss these findings in more depth by explaining them with relevant theories, comparing them with previous studies, and providing associated explanations of the possible causes.

7.1 Negative correlation between AI focus and firm performance

The current enthusiasm for AI makes it false to imagine that firms' high levels of AI necessarily increase organisational capability and performance. However, the results of this research do not support this hypothesis. On the contrary, this study has indicated that a high level of AI in businesses can lead to challenges instead of advantages in performance. These

especially include operational funding shortages, significantly restraining firm performance. For example, the results show that the regression coefficient is -0.313, which is statistically significant at the 1% level. In addition, the regression coefficient for AI focus is -0.020, and it is statistically significant at the 1% level. This suggests that a high level of AI focus in businesses significantly inhibits their financial performance. This could be attributed to the substantial investment required to develop AI technology, coupled with the generally longer return cycles for technological innovation activities. Therefore, during the initial stages of introducing AI, companies may be unable to realise substantial returns, thereby reducing the profitability of asset creation per unit, i.e., the total asset turnover. Such results challenge many prior studies' findings that highlighted the positive impact of AI on organisational performance, including financial, marketing, administrative aspects and process efficiency. Harnessing the inherent attributes of AI was believed to empower organisations to amplify the business value of their transformative initiatives.

According to economy theory, firms need cost justification and rational financial management so as to sustain the capabilities and resources required for safe operations and effective competition. However, the results have shown that a higher level of AI focus in firms often leads to financial risks that endanger firm performance. The result is consistent with the essential hypothesis of economic theory represented by managerial economics, which emphasises the safety of critical firm decisions (Barney and Clark, 2007). According to the results, the significant investment needed and the lengthier return cycles associated with technical innovation may make it difficult for firms to realise meaningful returns from AI adoption, at least during the early phases. This is consistent with the principles of managerial economic theory, which call for effective budget planning and evaluation in order to avoid blind decisions without considering the capabilities gained (Laosirihongthong, Prajogo and Adebajo, 2014). The research also recognises that high-tech resources, such as AI, possess attributes essential to a firm's competitive advantage, such as scarcity, imperfect imitability and lack of substitutability. In the study's context, these characteristics seem to

provide difficulties for AI acceptance, at least in its early phases. From a strategic standpoint, the study shows that despite the expected benefits of utilising AI's revolutionary powers, actual implementation presents difficulties, especially in terms of operational financing constraints and overall market performance.

Furthermore, the study's temporal perspective—which emphasises the longer return cycles for technological innovation—is consistent with the managerial economics theory principle that creating and applying essential resources (including technical innovations) may require some time to generate significant returns. The findings essentially highlight the difficulties and complications involved in incorporating high degrees of AI into enterprises, especially in the early stages. The adverse effects on financial performance underline the need for a sophisticated grasp of how organisational capacities, AI resources, and the long-term creation of competitive advantage interact in the rapidly changing context of the 4IR. This study suggests that the impact of AI focus on company performance is negative, possibly because these companies face more significant challenges caused by the sudden change in operations triggered by AI focus in the early stages. These challenges include technological implementation and investment (Dwivedi *et al.*, 2021), employee issues (Huang and Philp, 2021) and significant concerns about data privacy and ethics that impact daily operations (Eitel-Porter, 2021), which contribute to firms' inability to realise the short-term monetisation of AI assets and obtain corresponding financial returns.

Many companies encounter various technological implementation issues during the initial stages of implementing AI technology. For example, some researchers have found challenges related to low data quality during the initial stages of AI introduction. AI systems typically require large amounts of high-quality data for training and operation in areas such as machine learning, deep learning, etc. If an organisation's data quality is poor, including inaccuracies, incompleteness or biases, this may affect the performance of AI systems. Machine learning is the science of training computer programs or systems to perform tasks without explicit instructions (Raschka, Patterson and Nolet, 2020). Computer systems use machine learning

algorithms to process large amounts of data, identify data patterns, and accurately predict unknown or new scenarios. Deep learning is a subset of machine learning that uses specific algorithmic structures called neural networks, modelled similarly to the human brain. Deep learning attempts to automatically perform more complex tasks that typically require human intelligence. Both machine learning and deep learning require large amounts of high-quality training data to make accurate predictions (Ewuzie, Bolade and Egbedina, 2022). For example, machine learning models need about 50-100 data points for each feature, while deep learning models require several thousand data points for each feature. Thus, from the data, it is clear that as AI implementation has to deal with machine learning tasks, the practical implementation of AI algorithms is not straightforward. This creates substantial operational difficulties for business practitioners in implementing AI technology. According to Zaccone and Karim (2018), independent AI systems need to be built to perform operations in various fields. In frameworks like TensorFlow, programs are initially written in the Python language, and then the corresponding machine learning libraries are drawn upon to execute the models. The entire design and execution process of the program requires specialised human and other resources, resulting in significant expenses. For instance, when Google conducted large-scale neural network learning, it required a cluster with 255 computing nodes to individually train the AmoebaNet-B model with 5.57 billion parameters; each node is equipped with a chipset consisting of 1,024 TPUs (Zaccone and Karim, 2018). Therefore, successfully implementing AI is not an easy task.

Furthermore, these machine learning frameworks are challenging to integrate with existing databases, resulting in additional data conversion and transmission costs. AI training efficiency is also low. According to Zaccone and Karim (2018), existing AI systems lack execution optimisation techniques (such as large-scale caching, data chunking partitioning, indexes, etc.), significantly wasting computing and storage resources. It also increases the occurrence rate of program abnormalities (such as memory overflow and process blocking), severely affecting the efficiency of executing individual tasks. Traditional AI execution

methods also lack flexibility: chips (such as CPU, ARM, GPU, etc.) and algorithm optimisation (such as optimisation functions, evaluation metrics, etc.) need to be manually specified, increasing the demand for programming skills and making it challenging to maximise hardware resource advantages (Hofmann and Williams, 2017). Many AI tasks may be blocked without dynamic scheduling mechanisms until GPU resources meet the requirements, reducing overall execution efficiency. AI relies on high-quality training data, and traditional data governance work is complex, requiring significant human involvement and consuming a substantial portion of resources and time. Furthermore, large-scale machine-learning algorithms require a considerable amount of data for training. On the one hand, raw data from real scenarios often cannot be used directly, as they contain many missing values, errors and abnormal samples. On the other hand, a training set may have multiple data sources, and data source fusion presents issues such as inconsistent formats, excessive redundant information and high connection costs (Zhao *et al.*, 2021). These add huge costs and financial burdens to companies that adopt AI, which hinders the effectiveness of AI in promoting a company's financial profitability or financial performance.

Moreover, the added training costs in the initial stage of implementing AI are another reason why the introduction of AI technology may have a negative impact on company performance, given the requirement for internal employees to possess relevant skills. Understanding, operating and maintaining AI technology demands highly specialised skills and knowledge. The lack of these relevant skills can become an obstacle to implementing AI. Firstly, employees need to comprehend AI technology's basic concepts and principles. For instance, in the field of deep learning, employees need to grasp complex technical concepts such as neural network structures and algorithm optimisation (Zorzi *et al.*, 2015). Employees may struggle to comprehend and effectively apply AI technology without a solid understanding of these fundamental concepts. Companies typically need to invest substantial financial resources in hiring professionals to conduct employee training to achieve this goal. For example, companies need to enhance the learning and teaching of AI fundamentals. This

includes theoretical and practical aspects of core technologies like machine learning, deep learning, NLP, etc. This helps employees grasp AI technology's basic concepts, algorithms and tools. Through learning the fundamentals of AI, employees can understand the principles, scope of application and limitations of AI technology, providing technical support for the enterprise's digital transformation. Otherwise, AI technology cannot genuinely be integrated into the specific daily workflows of employees, potentially leading to errors. In addition, companies need to increase investment in training that is orientated towards particular enterprise needs. By combining practical scenarios, training should guide participants in applying AI technology to solve real-world problems. The necessity of practical exercises lies in their ability to help employees apply theoretical knowledge to real-world situations, enhancing their technical application capabilities (Davenport and Ronanki, 2018). Therefore, corporate training is a crucial initiative that requires top-level technical experts and mentors to provide professional guidance and consulting services. It also necessitates a range of training facilities and hands-on experiences to reinforce employees' knowledge and skills in AI.

Moreover, when enterprises adopt AI, they need to consider regulatory risks such as privacy, and addressing these risks requires significant technological and managerial investment. This can have a negative impact on company performance. For instance, the People's Republic of China has taken the lead in AI regulation by introducing and implementing a series of regulations (Lucero *et al.* 2020), including the Internet Information Service Algorithm Recommendation Management Regulations (Algorithm Recommendation Regulations), effective from March 1, 2023; the Internet Information Service Deep Synthesis Management Regulations (Deep Synthesis Regulations), effective from January 10, 2023; the Interim Measures for the Management of Generative AI Services (Generative AI Measures), announced on July 13, 2023 and effective from August 15, 2023; and the Technology Ethics Review Measures (Trial) (Draft for Solicitation of Comments) (Ethics Review Measures (Draft)), which publicly solicited opinions on April 14, 2023, with feedback accepted until

May 3, 2023. As discussed in the article “The Great Transformation of Global AI Governance: An Overview and Implications of the EU AI Governance Regulatory Framework”, the EU's Artificial Intelligence Act (referred to as the "AI Act") classifies AI systems into unacceptable risk, high risk, limited risk and minimal risk categories, taking a risk-based approach. For each category of AI systems, the AI Act adopts different regulatory strategies supported by specific provisions for enforceable regulation. Specifically, for AI systems classified as an unacceptable risk, the EU prohibits any deployment by businesses or individuals (Madiaga, 2021). For high-risk AI systems, the EU allows relevant entities to market or use them after fulfilling obligations such as pre-assessment, with continuous monitoring during and after use. Although the EU does not require the same entities to fulfil pre-assessment obligations for limited-risk AI systems, they still need to comply with corresponding transparency obligations. As for minimal-risk AI systems, the entities involved are free to deploy and use them at their discretion. Overall, AI system regulation should not come at the cost of sacrificing or abandoning the development of AI technology. In practice, enterprises generally incur high costs or burdens to provide high-risk AI systems that comply with market regulations. Small and medium-sized enterprises, due to various constraints such as financial resources, market share and capabilities, may find it challenging to meet these requirements. Therefore, the AI Act also proposes strategies such as AI regulatory sandboxes, encouraging the development and innovation of all enterprises, especially small and medium-sized enterprises.

In summary, the negative relationship between initial obstacles and financial performance highlights how difficult it may be to overcome these issues, which might range from expensive regulatory compliance to technical implementation difficulties. The results stress how crucial it is to have a strategic grasp of how AI affects organisational capabilities and long-term competitive advantage, and they demonstrate that it is essential for companies to carefully weigh the challenges of integrating AI for best results.

7.2 Partial mediating effect of R&D staff ratio

According to the research results, the R&D staff ratio serves as a partial mediator between AI focus and firm performance. Specifically, a higher level of AI focus is correlated with an increased presence of technical personnel in the company, implying a substantial increase in firm costs, often resulting in a decline in financial performance. This can be elucidated through the lens of DCT, which requires firms to make rational decisions when adopting change management (including AI). As discussed in the literature review, dynamic capabilities pertain to a company's adeptness at integrating, constructing and adjusting both internal and external resources and competencies to navigate evolving business landscapes (Teece and Pisano, 2003). The primary objective is to achieve exceptional returns. These capabilities reflect how swiftly and to what extent a company's distinctive resources and competencies can be tailored to align with the opportunities and demands of the business environment (Teece, 2010). In contrast to specific fixed assets that facilitate organisational capabilities, R&D personnel represent a more dynamic source of organisational capability, enhancing organisational adaptability. However, they also constitute one of the most uncontrollable cost sources. This implies that increasing the proportion of R&D personnel will increase the company's financial burden, although it enhances the company's dynamic adjustment capability in the long run. However, in the short term, the beneficial effects of this strategy are limited. From a dynamic capabilities perspective, a higher proportion of R&D personnel adds costs, negatively impacting the role of AI focus in the market performance of firms. This result challenges the prior research findings that added investment in R&D and talent cultivation can positively impact firms' market and operational performance (e.g. Alam *et al.*, 2020).

Several reasons may explain this difference in findings in the context of AI implementation. Firstly, introducing and maintaining a high level of AI technology, including technical personnel, requires a large amount of capital investment, which will affect the overall cost of the enterprise, thus negatively affecting financial performance. In many prior studies, the

research results indicate that personnel are among the most significant expenses in modern business. In the process of developing and maintaining AI technology, the proportion of R&D personnel increases; this causes increased costs in areas such as personnel training, maintenance, recruitment and promotion. Specifically, this possibility comes from several different sources. For example, if the source of R&D personnel is mainly external, the increased costs will come from salaries and retainment, as well as additional training to adapt to the company's environment and culture. At the same time, existing technology teams may need to upgrade their skill levels to accommodate the introduction of new high-level AI technologies, which may include learning new programming languages and data science techniques and adapting and optimising AI models. The process of training existing employees may thus result in a specific cost increase. These are all possible factors leading to reconciliation between the differing results. A high proportion of R&D personnel may act as a mediator, influencing the performance of AI and benefiting firms' market performance. Some other studies (e.g. Nadikattu, 2020) also indicate that introducing complex AI systems may require more technicians to manage, maintain and optimise the system's performance: data scientists, machine learning engineers, algorithm experts, etc. Moreover, the implementation of AI technology cannot be achieved overnight, so it is likely that during the transition period, the technical team may need to spend a lot of time understanding, integrating and testing the system, which may lead to less investment from the technical staff in other aspects of the business. To ensure that the introduced AI technology can run smoothly, companies may also need to hire external professionals or consulting firms to provide additional support and guidance, which can also increase costs. While these additional inputs and costs may negatively impact a company's financial performance in the short term, the company is expected to achieve better performance in the long term as technicians adapt to new technologies and improve their effectiveness.

Secondly, a contributing factor to this situation could be the extended timeframe required for AI investments compared to other innovation ventures. The efforts of AI R&D personnel

demand additional time and space to amalgamate and yield the desired outcomes. In other words, due to the ongoing developmental phase of AI technology, AI R&D personnel management within the realm of HRM is also at a relatively immature stage. Consequently, an increase in AI R&D personnel may not only lead to escalated costs. Still, it may also result in a lack of beneficial output due to the enterprise's inability to proficiently apply personnel management methods, at least within a specific timeframe. This impact may stem from the time lag associated with the efforts exerted by R&D personnel. Some scholars (e.g. Dwivedi *et al.*, 2021) have noted that the research process is time-consuming, and the effects of current AI R&D may not be manifested in measured productivity until several years have passed. The National Innovation System consists of a network of interconnected policies, institutions and organisations, wherein innovative performance relies not solely on the isolated performance of individual components but also on the quality of interaction and collaboration among various elements (Tsai, 2009), subject to dynamic processes. Consequently, the transformation process from innovation input to output may experience delays due to the intricate interplay of factors such as personnel interactions, collaboration and communication issues, influencing the effects of AI implementation on firm performance. R&D investment and staff ratio may not immediately translate into innovation output and profits, or there may be a multi-period impact of one-time innovation input on output.

In conclusion, the current study's findings show that a higher degree of AI focus is correlated with a more significant presence of technical staff, which in turn causes a reduction in financial performance. DCT, which stresses the need for a company's capacity to adjust internal and external resources to traverse changing business environments, may be used to understand this. Although a higher percentage of R&D staff improves the organisation's capacity for dynamic adjustment over the long term, it comes at an immediate cost to the business. Significant financial expenditure is needed to adopt and keep cutting-edge AI technology, which raises total expenses. The results contradict earlier studies that suggested higher R&D spending had beneficial effects on market and operational success. The longer

time horizon for AI investments and inexperienced staff management in AI R&D further add to the expenses and postponed benefits. The results demonstrate how complex connections between employees, problems with teamwork and communication barriers all interact to affect how AI deployment affects business performance.

7.3 Partial mediating effect of R&D investment

This study found that R&D investment did play a partial mediating effect in the relationship between AI focus and firm performance. This finding echoes the findings of many prior studies. For example, Son and Zo (2023) found that a positive impact on firm performance was observed when SMEs possessed adequate R&D resources (technological, human and financial) and maintained continuous R&D investment. Specifically, SMEs with more significant financial resources, reflected in increased R&D investment, exhibit enhanced firm performance through heightened external R&D collaboration, as Zhang, Li and Li (2022) found. The motivation for external collaboration may arise from either fewer technological resources or an abundance of financial resources within SMEs. To enhance firm performance, tailored open innovation strategies need to be implemented based on the specific characteristics of R&D resources in SMEs (Marullo, Piccaluga and Cesaroni, 2020). Therefore, R&D investment, as an essential factor, can influence firm performance in terms of benefiting from AI as a new technological disruption. Thus, the present study's findings show that R&D investment influences firm performance by mediating the relationship with AI focus, which corresponds with prior studies.

In our study, the results can primarily be explained using DCT. As discussed in the literature review, the initial characteristic of dynamic capabilities for a firm is that a company's capabilities should be developed (Teece, 2014). A firm's dynamic capabilities should enable firms to adjust and readjust themselves to fit in with varied business contexts and environments (Gremme and Wohlgemuth, 2017). Hence, the dynamic capabilities of a firm should be established based on steady and continuous organisational investments in R&D.

Increased R&D in AI technology development can help firms form the distinctive abilities of sensing, seizing and transforming, which are the crucial characteristics of firms that empower them to adapt and coevolve in tandem with the business environment. A study by Martinez-Sanchez *et al.* (2020) found that firms with a higher R&D investment proportion tended to obtain a higher absorptive knowledge capacity and enhance their own capabilities in change management. These results can help explain why increased R&D investment by firms can be a positive mediator in the relationship between AI focus and firm performance from different perspectives.

Firstly, as analysed previously, employee resistance to change is one obstacle that prevents enterprises from fully taking advantage of AI focus in fostering firm performance. This resistance may result from firms' inefficiency and lack of flexible organisational capability to adapt to changes (Yukl and Lepsinger, 2005). If firms' capability to adapt to and manage change can be improved, the organisation's capability to positively take advantage of AI focus to foster organisational performance can also be harnessed (Yukl and Lepsinger, 2005). Increased R&D, from the perspective of dynamic capabilities, is perceived to be beneficial in improving the flexibility of operations, whether in HRM, marketing, or the supply chain. In highly dynamic market conditions, influenced by various technological disruptions, firms' emphasis on R&D also contributes to the knowledge bases that form the sources of dynamic capabilities (Prieto and Easterby-Smith, 2006). Such knowledge-based organisational capability is significant in harnessing firms' ability to handle changes and market dynamics. As explained by Rahimli (2012), a company's competitive edge can be significantly enhanced by effectively blending external and internal knowledge resources, and the KBV can offer insights into why certain firms excel in this aspect compared to others.

Another critical factor in the importance of R&D in enhancing knowledge is the uneven distribution of knowledge across firms. From a knowledge-based perspective, increased R&D can improve firms' capability to foster AI utility to trigger enhanced firm performance. Managing knowledge strategically is crucial, especially when it comes to tacit knowledge,

which is challenging to observe and articulate for subsequent utilisation, making it less susceptible to imitation by rival firms (Rahimli, 2012). This indicates that organisations engaging in broader searches may foster superior knowledge by enhancing diversity, potentially leading to the creation of more unique knowledge combinations, including in the AI domain. The organisational context plays a pivotal role in shaping knowledge creation, influencing employees' ability to seek and integrate both internal and external knowledge (Nonaka and von Krogh, 2009). Companies thus have to invest in knowledge and AI technology to break down such unevenness and improve the organisational knowledge base because AI's positive and potential role in enhancing firm performance depends on firms' capacity in knowledge management and change management.

However, the strategic role of R&D in mediating the relationship between AI focus and firm performance should be assessed in the context of market lag. Market lag, the delayed influence of R&D activities and expenditure on company performance to achieve specific outcomes is thought to be minimised by R&D investment. This means that firms cannot avoid market lag, but increased R&D can weaken its effects, thus positively mediating the role of AI focus in enhancing firm performance (Bae, Kim and Oh, 2017; Parcharidis and Varsakelis, 2007). According to Minniti and Venturini (2017), the market or time lag effects of R&D can negatively impact decision-makers when assessing the effects brought about by R&D, thus influencing decision-making accuracy. In addition, the reasons that lead to such time lags or delays, as demonstrated by Lome, Heggeseth, and Moen (2016), are usually the complexity of knowledge transfer and application in a company. For example, the complexities of applying AI technology in large firms can be deemed as one crucial factor causing the market or time lag of R&D. This will lead to the result that R&D effects cannot be detected. As highlighted by Griffith, Harrison and Van Reenan (2006), there is an optimistic view of the effects of R&D investment in harnessing firms' capability in development ability. As Del Canto and Gonzalez (1999) pointed out, there is a detrimental impact of R&D investment on organisational capability and asset turnover, which is

statistically significant at the 10% level. Moreover, a positive effect is observed even during the lag period, reaching significance at the 1% level in the second lag period, according to Del Canto and Gonzalez (1999). Furthermore, R&D investment contributes to cost and efficiency optimisation, improving the operational capability of AI technology applications, even during the lag period. Investing in R&D is essential for designing easily manufactured products and optimising production processes. Nevertheless, excessive spending on R&D goes against the principle of stringent cost control and could result in unnecessary financial burdens (Guo, Wang and Wei, 2018). Therefore, when devoting efforts to R&D, it is essential to avoid excessive R&D that cannot be effectively translated into large-scale production since this would also lead to a waste of resources.

While R&D is generally believed to have positive long-term impacts on firm performance, the specific effectiveness of AI focus in benefiting profitability is less clear, not least because it is highly dependent on the focus area or domain of R&D undertaken by the firms. Suppose the firm's AI R&D does not accurately address the bottleneck issues in AI application for the company but instead concentrates on other areas, rendering the R&D ineffective or lacking a mediating effect on the impact of AI on firm performance. In that case, practitioners should note that this kind of irrelevance can directly lead to ineffective results. Suppose companies adopt independent methods when introducing AI that are not directly influenced by R&D investment. In that case, the R&D investment may not be able to perform a positive role in mediating the relationship between AI focus and firm performance. In other words, even though companies invest significantly in R&D, independent methods such as outsourcing adopted by companies in the realm of AI may result in a lack of correlation. This study did not thoroughly explore these factors, making them potential influencers on the research outcome. Measurement inaccuracies or incompleteness in assessing R&D investment could also be a contributing factor, making it challenging to capture its actual mediating effect. If there are biases or omissions in the measurement methods, accurately evaluating R&D investment's mediating role in the relationship between AI focus and firm performance

becomes difficult. To gain a more comprehensive understanding of this result, further research into these potential reasons and more refined data analysis may be necessary.

In conclusion, the findings show that R&D investment plays a primary mediating function in the complex link between AI focus and firm performance. The results of this study support the idea that in the context of AI as a disruptive technology, customised open innovation strategies based on specific R&D attributes might affect business performance. It is proposed that increased R&D in AI technology would provide businesses with unique skills like perceiving, seizing and transforming—all necessary for adaptive coevolution. In very dynamic market conditions, a focus on R&D strengthens organisational capacities based on knowledge, explaining why certain companies successfully integrate internal and external knowledge resources. Increased R&D spending lessens the consequences of market lag, even if unavoidable, showing how dynamic AI–firm connections are over time. Notwithstanding these discoveries, the research notes many possible drawbacks, such as the difficulty of applying and transferring knowledge in AI technology, inaccurate measurement and the narrow emphasis of AI R&D. It urges practitioners to match their R&D efforts with the unique requirements of AI applications for efficient mediation, warning against the dangers of meaningless R&D and autonomous AI approaches.

7.4 Moderating effect of top manager education level

The results of the present study indicate that when the educational level of top managers increases, the negative correlation between AI focus and market performance for businesses diminishes. In other words, as the educational qualifications of senior executives rise, the adverse impact of utilising AI on market performance decreases. This implies that higher educational qualifications among executives can enhance the likelihood of a positive effect of employing AI technologies on firm performance or at least mitigate the negative impact. This outcome can be explained and analysed through the lens of TMT. As previously discussed in the literature review, talent management is a crucial aspect of strategic human resources,

involving activities such as recruitment, retention, development, rewards and performance optimisation (Acar and Yener, 2016). Talent management recognises human capital as the most valuable resource for a company (Dorasamy, 2021). Strategic implementations in talent management focus not only on identifying and developing abilities but also on nurturing promising employees, understanding that it involves more than just skill development (Greene, 2020; Soheli-Uz-Zaman *et al.*, 2022). This encompasses facilitating the advancement of talented employees within the organisation, allowing them to demonstrate their potential and capabilities. As shown by Davies and Kourdi (2010), supporting talents play a vital role in executing activities and providing assistance in non-core business functions that may be suitable for automation. The systematic categorisation of talents allows organisations to strategically oversee and utilise the diverse skills of their workforce, reducing the barriers and costs associated with adopting and implementing AI technology. Leaders with higher educational qualifications are proven to exhibit a greater inclination towards professionalism, handling matters, addressing issues and leading people to implement AI based on an expanded mindset and enhanced skills (Murphy and Reichard, 2012). In summary, the educational qualifications of executives not only contribute to reducing the negative impact of AI and focusing on market performance but also play a pivotal role in fostering the positive and effective implementation of AI within organisations.

In the context of AI technology utilisation, talent becomes crucial in enhancing the positive effects of AI. For instance, the higher educational qualifications of executives are associated with a higher ability to embrace new technologies, thereby reducing the time and cost spent on training highly educated management talents and hiring advanced AI training professionals. Consequently, top managers' educational level can reduce companies' substantial costs in investing in AI, leading to improved market performance and profitability. In the study by Deem *et al.* (2007), higher education tended to provide executives with a solid academic and practical knowledge base. Thanks to this knowledge foundation, they could easily absorb and comprehend the fundamentals and uses of cutting-edge technology, such as

AI technology. In addition, their higher education level usually improved their critical thinking and problem-solving capacity. Therefore, when faced with implementation and operational problems in the initial stage of adopting AI technology, executive leaders with higher education levels tend to find more workable solutions to resolve them (Stahl *et al.*, 2012). This will help reduce the possibility of AI implementation failure and upgrade the success rate, which can mitigate the adverse effects of AI focus on firm performance. This is why Soheli-Uz-Zaman *et al.* (2022) stated that more highly educated executives could decipher complicated technical problems, make wise choices and create workable plans for implementing AI technology.

Elevated skills and educational cognition also enable senior managers to play a constructive role in guiding staff who may resist or be unfamiliar with new AI technologies or AI-driven devices. As has been analysed above, one possible cause that leads to the negative correlation between AI implementation and firms' market performance is staff resistance to or unfamiliarity with the technology, which adds to the training costs for firms in the process of implementing AI techniques. In other words, senior executives with higher educational qualifications tend to have a broader HRM knowledge (Elmuti, Minnis and Abebe, 2005). This includes understanding how to adopt various leadership and management styles to effectively guide, instruct and motivate employees. This knowledge enables them to reduce resistance towards AI by encouraging employees to approach AI technologies more positively. While the leadership skills of executive leaders may stem from their inherent traits, many scholars believe that their leadership and management capabilities can also be influenced by education and teaching. Crawford *et al.* (2002) conducted a review of more than 40 graduate degree programmes concentrating on leadership studies. The rising demand for leadership education is also fuelled by the interest of non-traditional students, such as executives and practitioners (Crawford *et al.*, 2002). Academic entities like the Harvard Business School Executive Education Program, dedicated to enhancing the leadership capacities of executives, and the University of Michigan's Michigan Leadership Program

(MLP), known for developing leadership skills with a specific focus on critical leadership issues, exemplify this trend. Therefore, higher education can have a moderating effect on the role of AI focus in influencing the firms' market performance, as it helps to improve AI change management effectiveness from the HRM perspective.

Furthermore, executives with higher educational qualifications tend to possess a broader knowledge base and skills in continuously updating their knowledge to keep pace with societal changes. This includes their ability to educate themselves and stay informed about the evolving regulatory policies on privacy and data security concerning the adoption of AI technology in firms, thereby enhancing their capabilities in managing regulatory risks. According to a study by Benbya, Davenport and Pachidi (2020), executives with higher educational qualifications can conduct a more comprehensive analysis of the various risks faced by the company in AI technology developments and adopt corresponding strategies to mitigate these risks. For example, in the AI domain, leaders with higher educational qualifications tend to have more comprehensive resources and channels to keep updated with changes in regulatory messages, thus improving efficiency in adjusting firms' AI practices and internal settings to deal with the associated risks. According to Birkstedt *et al.* (2023), the complexity of global AI regulatory policies, influenced by market diversity and the cross-cultural impacts of societal and cultural development, requires executives with rich knowledge and experience to assess the risks posed by these changes. Executives with higher educational qualifications may possess the knowledge and expertise to effectively manage and protect the privacy of customers, employees and business data (Birkstedt *et al.*, 2023). They understand privacy regulations and can formulate and implement corresponding privacy protection strategies, thereby reducing the risks of non-compliance and data breaches. Consequently, this can lower the costs associated with maintaining AI's smooth and regulation-compliant operation, reducing the likelihood of AI project management failures.

Overall, the unfavourable relationship between a company's ability to compete in the market and its use of AI is lessened when top managers have more education. TMT, which

emphasises the strategic importance of human resources in recruitment, retention and development, can explain this beneficial effect. Higher levels of education are linked to an executive's greater capacity to adopt new technologies, which lowers training expenses and promotes the effective use of AI. Higher education gives leaders a strong foundation in information, the ability to think critically and the capacity to solve problems. These qualities help them to effectively manage the complexity of AI technology and maximise its benefits for improving market performance. More highly educated leaders may also have a positive influence in helping workers embrace AI by lowering opposition and training expenses. In addition, more highly educated executives have a more comprehensive knowledge base and consistently improve their abilities, which makes them better equipped to handle the regulatory concerns that come with the deployment of AI. They are able to manage the intricacies of international AI regulatory rules, implement appropriate methods and carry out thorough risk analyses.

7.5 Chapter summary

To conclude, this chapter offers further analysis and discussion of the research findings presented in the previous chapter. Through this analysis, it becomes evident that the relationship between AI and firm performance is complex, involving financial investments and HRM. The educational attainments of top managers, R&D investment and the R&D staff ratio emerge as crucial factors contributing to the success of AI development, although their impact may vary in different situations. The data analysis results are the same as the theoretical expectations: this study suggests that top manager education level, investment in R&D and the R&D staff ratio significantly influence the relationship between AI focus and its impact on a firm's market profitability. It is crucial to emphasise that when initiating AI programs, firms must meticulously handle HRM, focusing on talent acquisition, especially executives with higher educational qualifications. Simultaneously, firms must carefully assess the overall costs associated with implementing AI and determine their ability to bear these high costs in the short term. Recognising that AI investment returns may require

extended time is essential for informed decision-making.

CHAPTER EIGHT: CONCLUSIONS, IMPLICATIONS AND CONTRIBUTIONS

8.0 Introduction

This concluding part of the thesis briefly summarises the research's leading theoretical and managerial implications and academic contributions to theory and practice. It also discusses the limitations and suggests avenues for future research. Finally, it provides a chapter summary and conclusion.

8.1 Theoretical implications

8.1.1 Impact of AI focus on firm performance: theoretical insights

The research findings underscore a nuanced relationship between AI adoption and firm performance metrics such as ROA and Tobin's Q. While initial expectations often posit that AI technologies will inherently improve organisational efficiency and profitability, empirical evidence suggests varying outcomes depending on implementation strategies and contextual factors (Davenport & Ronanki, 2018). This challenges simplistic assumptions and calls for a deeper understanding of the conditions under which AI investments yield optimal results.

Theoretically, this study expands the discourse on technological adoption by illustrating that AI, unlike traditional IT investments, requires a more sophisticated integration strategy considering the firm's existing capabilities, market position, and strategic objectives. For instance, firms with a higher AI focus might experience initial performance declines due to these technologies' disruptive nature, necessitating a period of adjustment and learning (Brynjolfsson & McAfee, 2014). This finding aligns with the theory of disruptive innovation, which posits that new technologies can initially underperform established ones but eventually surpass them as they evolve and firms adapt (Christensen, 2013).

8.1.2 Role of research and development (R&D): theoretical perspectives

Research and Development (R&D) expenditure emerges as a critical mediator in the AI-focus-firm performance relationship. While R&D investments are pivotal for fostering long-term innovation capabilities, their immediate impact on financial performance can be disruptive due to increased costs and organisational adjustments (Saberri & Yusuff, 2012). This dual role highlights the complexity of balancing short-term financial pressures with long-term strategic goals in AI adoption strategies.

From a theoretical perspective, the findings contribute to the firm's Resource-Based View (RBV), emphasising the strategic importance of investing in unique, valuable, and difficult-to-imitate resources (Barney, 1991). R&D investments in AI represent such resources, providing firms with a competitive edge through innovation and differentiation. However, the study also reveals the challenges associated with these investments, such as the need for continuous learning and adaptation, aligning with dynamic capabilities theory, which stresses the importance of organisational agility and responsiveness to changing environments (Teece, Pisano, & Shuen, 1997).

8.1.3 Influence of senior executives' education level: theoretical underpinnings

The educational background of senior executives plays a crucial moderating role in mitigating the adverse effects of AI adoption on firm capabilities. Senior leaders with higher educational qualifications are better equipped to navigate the complexities of AI integration, facilitate organisational learning, and align AI initiatives with broader strategic objectives (TMT theory). This underscores the importance of human capital in shaping the outcomes of technological investments within organisations.

This study extends the Upper Echelons Theory, which posits that organisational outcomes are partially predicted by the characteristics of its top managers (Hambrick & Mason, 1984). The

findings suggest that senior executives with advanced education are more adept at leveraging AI technologies to enhance firm performance, supporting the notion that managerial cognition and knowledge significantly influence strategic decision-making processes. Moreover, the study highlights the role of continuous executive education and training in maintaining a competitive advantage in rapidly evolving technological landscapes.

8.2 Managerial implications

8.2.1 Strategic planning for AI adoption: managerial recommendations

Effective strategic planning is essential for maximising the benefits of AI adoption while minimising associated risks. Managers are advised to adopt a systematic approach that includes rigorous evaluation of AI technologies, clear articulation of implementation goals, and proactive management of organisational change processes (Davenport & Ronanki, 2018). This approach helps harness AI's transformative potential while safeguarding against pitfalls such as escalating costs and operational disruptions.

Managers should also focus on developing a robust AI strategy that aligns with the overall business strategy, ensuring that AI initiatives support core business objectives and drive value creation. This involves conducting thorough cost-benefit analyses, engaging stakeholders across the organisation, and fostering a culture of innovation and experimentation. By embedding AI within the strategic planning process, firms can create a roadmap for successful AI integration that addresses potential challenges and leverages opportunities for competitive advantage.

8.2.2 Importance of senior executives' education: managerial strategies

Recruiting and retaining senior executives with strong AI knowledge and higher educational credentials are critical for successful AI adoption. Educated leaders not only facilitate smoother integration of AI technologies but also foster a culture of innovation and continuous

learning within the organisation (Saber & Yusuff, 2012). By leveraging internal expertise, organisations can reduce dependency on external consultants and accelerate the adoption curve of AI-driven innovations.

Managers should prioritise executive development programs that enhance senior leaders' AI literacy and strategic thinking capabilities. This could involve partnerships with academic institutions, participation in industry forums, and investment in ongoing training programs. Additionally, fostering an environment that encourages cross-functional collaboration and knowledge sharing can help disseminate AI-related insights and best practices throughout the organisation, driving collective competence in AI utilisation.

8.2.3 Prudent AI investment strategies

Based on the empirical insights, the thesis recommends that firms adopt a cautious and strategic approach to AI investment. Managers are advised to conduct thorough cost-benefit analyses and risk assessments before committing substantial resources to AI initiatives. This approach involves not only evaluating the potential financial returns but also considering the organisational readiness and capacity to manage the disruptive effects of AI adoption.

Strategic planning should include provisions for mitigating risks such as operational disruptions, cybersecurity threats, and ethical considerations associated with AI technologies. By anticipating these challenges and integrating risk management frameworks into AI adoption strategies, firms can enhance their resilience and minimise potential negative impacts on performance.

8.3 Research contributions

8.3.1 Theoretical contribution to AI literature

This study significantly contributes to the theoretical understanding of AI adoption by integrating empirical evidence on AI focus, R&D investments, managerial education, and firm performance. By elucidating the complex interplay between these variables, the research expands existing knowledge and offers new insights into the strategic governance implications of AI technologies in organisational contexts.

The research bridges gaps in the literature by providing a comprehensive analysis of how AI adoption affects firm performance through mediating and moderating mechanisms. This integrative approach enriches the theoretical framework surrounding AI adoption, offering a more holistic understanding of the factors influencing its success. Furthermore, the study's findings highlight the importance of contextualising AI adoption within broader strategic and organisational dynamics, contributing to a more nuanced and sophisticated theoretical discourse.

8.3.2 Methodological advancements

Methodologically, the study employs advanced statistical techniques and mathematical models to quantify the impact of AI adoption on firm performance. By rigorously analysing data from Chinese listed companies, the research enhances the methodological toolkit available for studying the effects of technological innovations on business outcomes. This methodological rigour strengthens the reliability and validity of the study's findings, contributing to the robustness of AI adoption research in management and economics.

Using sophisticated econometric models and longitudinal data analysis techniques allows for a more accurate assessment of causal relationships and temporal dynamics in AI adoption. This methodological contribution is particularly valuable for future researchers seeking to

replicate or extend the study, providing a solid foundation for empirical investigations into the strategic impacts of AI technologies. Additionally, the study's methodological approach can be adapted to different contexts and industries, facilitating cross-comparative research and broader generalisation of findings.

8.4 Research limitations and future research

The main limitation of this research comes from the nature of regression analysis, which is built on the rigid (although concise) analysis of samples. Regression analysis based on the limited samples of this research could risk biased conclusions, as the data collected from the two databases used by the researcher represent only a small part of the sea of information in stock markets worldwide. Another limitation of the research derives from the limited variables involved in the analysis, creating a risk of incomplete findings by the research regarding the highly complicated nature of business performance.

Secondly, the limitations of the research sample selection can also be reflected (Saberi and Yusuff, 2012). For example, this study selected most of China's listed companies but did not conduct a more detailed industry classification study, and the research area coverage selected only China. Future research could consider segmenting the companies by industry and could focus on data from some other countries besides China for verification. Therefore, these findings are provisional and further research is needed before any firm conclusions can be drawn.

The above weaknesses of the study suggest that future research could expand the range of variables and test their interactions, for example, by examining the impact of AI focus on the performance of small and medium-sized enterprises or by testing models with comparable processes and in different countries. In the future, it may also be possible to distinguish between automated and innovative AI terms and examine their corresponding impacts on performance. In addition, according to Davenport *et al.* (2020), the impact of AI's focus on marketing is on the packaging of consumer goods, retail, banking, tourism, and other

industries. Therefore, future studies could also continue to conduct industry-level comparisons in the form of case studies.

In addition, future empirical studies could expand the dimensions of AI and firm performance, such as employee happiness and dedication, retention rates or organisational success, which are also important aspects that are directly or indirectly related to firm performance. In terms of the dimension of firm performance, the impact of AI on social performance could also be developed in the future. Although the research shows that the implementation of AI has the potential to improve firm performance, the effectiveness of the use of AI may vary depending on national policies, business environments and business types. Therefore, future research on the influencing factors of AI focus on firm performance is crucial and could develop more factors that are not covered and analysed in this research.

8.5 Chapter summary

To summarise, AI capacity is the comprehensive ability of today's organisations to develop and compete within an external fast-paced environment of AI innovation and application. This research, based on regression analysis of the main variables related to AI focus, senior manager education level, R&D investment and R&D staff ratio, ROA and Tobin's Q ratio, etc., has probed deeper into the impact of these variables on the performance of listed firms in China. According to the results, top managers' R&D and higher education levels have partial mediating and moderating effects on firm performance, respectively. Moreover, they may create broader opportunities for further organisational development. Overall, maintaining a high level of AI focus, R&D investment, R&D staff ratio and the education level of top managers is crucial for modern enterprises. This is expected to bring long-term benefits.

8.6 Conclusions

This thesis defines the measurement standards for AI focus, divides the different words relating to AI terminology into three aspects (mechanical AI, feeling AI and thinking AI) and conducts a hierarchical study of AI focus from low intelligence to high intelligence. In

addition, it establishes a model to study the direct impact mechanism of AI focused on the performance of Chinese listed companies; at the same time, it examines top manager education level, R&D investment and R&D staff ratio.

A rigorous two-staged methodology was implemented to explore the operational aspects of this study in more depth. The initial foundations were laid with a careful qualitative synthesis of the existing literature, which helped understand AI focus and how it might affect firm performance. Continuing from this point, the research took an exploratory approach by analysing the annual reports of Chinese-listed companies for the period ranging from 2014 to 2022. This innovative approach offered valid initial data correlating AI focus and firm performance. Finally, the study rigorously validated its model by integrating appropriate financial information and leveraging the sophisticated functionalities of STATA statistical software. This in-depth empirical study enabled confirmation of the theoretical framework and demonstrated a negative correlation between AI focus and firm performance. This study is the first to conceptualise AI focus and its antecedents, mediators, moderators and consequences (based on firm performance).

This examination enhances the knowledge of AI focus and firm performance through theoretical extension, measurement, and testing. For example, in order to study the impact of AI focus on firm performance, this study categorises AI focus from three different perspectives (mechanical AI, thinking AI and feeling AI). It also advances the theory by proposing a new framework elucidating the relationship between AI focus and firm performance, underpinned by economic theory, DCT and TMT. Finally, this study provides a clear understanding of AI focus, which can support companies more likely to increase corporate AI focus through senior manager education level, R&D investment, and R&D staff ratio.

This paper's results show a significant negative relationship between the AI focus and firm performance of listed companies in China. In terms of R&D, the staff ratio of R&D and

investment in R&D have both been shown to play partial mediating effects in the relationship between AI focus and firm performance. Secondly, senior manager education level has been shown to play a moderating role in the relationship between AI focus and firm performance. In addition, the study further analysed the specific impact of the three dimensions of AI focus on firm performance. The results show that the three component indicators negatively correlate with firm performance. Among them, feeling AI has the most significant impact on firm performance, followed by thinking AI and finally mechanical AI.

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Appendices:

Appendix 1 An overview of existing AI and firm performance papers

(Notes: BDA, Big Data analytics; BDACs, Big Data analytics capabilities; DCT, dynamic capabilities theory; DCV, dynamic capabilities view; IoT, Internet of Things; NLP, natural language processing; RBV, resource-based view; SMEs, small and medium-sized enterprises).

No.	Publication	Source	Title	Aim / Objective	Key theories/Model	Key argument	Key relationships	Sample	AI technology	Method	Key Findings
2022											
1	Ahmed <i>et al.</i> (2022)	<i>International Journal of System Assurance Engineering and Management</i>	Business boosting through sentiment analysis using an artificial intelligence approach	To investigate how AI can enhance business performance through sentiment analysis	Machine learning and deep learning theory	AI technologies, including sentiment analysis and machine learning techniques, can boost a firm's performance and improve customer experience.	AI →customer experience/service AI →product improvement AI →future emergency	/	Machine learning and deep learning (Sentiment analysis/unstructured text)	Perspective paper	AI methods in the application of machine learning and deep learning, especially sentiment analysis, are valuable tools to enhance business performance.
2	Bag <i>et al.</i> (2022)	<i>Journal of Business Research</i>	Effect of eco-innovation on green supply chain management, circular economy capability, and performance of small and medium enterprises	To explore enablers in the context of SMEs' contribution to the circular economy through the lens of institutional and dynamic capabilities view theories.	Institutional theory and DCV	There is a lack of evidence in the current literature reflecting the contribution of SMEs to circular economy developments	Coercive pressures →Eco innovation in SMEs Normative pressures → Eco-innovation in SMEs Mimetic pressures → Eco-innovation in SMEs Eco-innovation → Green supply chain management (GSCM) practices in SMEs Eco-innovation → Circular economy (CE) adoption in SMEs GSCM practices → CE adoption in SMEs GSCM practices →	240 workers working in small and medium-sized enterprises in the South African manufacturing industry	Machine learning and deep learning (Big data analytics)	Empirical – survey	GSCM has a positive impact on CE capability. BDSCs have a moderating effect on the relationship between CE adoption and firm performance in the circular economy supply chain but no impact on the relationship between GSCM and performance.

							Firm performance for CE supply chain in SMEs CE adoption → Firm performance for CE supply chain in SMEs Higher/lower strength of BDSCs → GSCM practices on firm performance The higher/lower the strength of BDSCs → CE adoption on firm performance				
3	Barbosa <i>et al.</i> (2022)	<i>International Journal of Business Environment</i>	Supply chain collaboration and organisational performance: the effects of big data analytics capabilities, technological dynamism, and competitive intensity	To assess the effects collaboration has on organisational performance, especially when mediated by BDACs	Relational view theory	Previous research has ignored the effects that inter-organisational collaboration could have on supply chain relationships.	Collaboration → Organisational performance Mediator: BDACs Collaboration → Organisational performance by increasing perception of value Collaboration → Organisational performance by increasing order fulfilment performance Collaboration → Organisational performance by increasing financial performance Inter-organisational collaboration → Organisational performance Moderators: Technology dynamism, competitive intensity	323 Brazilian retail companies	Machine learning and deep learning (Big data analytics)	Empirical – survey	Collaboration directly affects organisational performance, mediated by BDACs and moderated by technological dynamism and competitive intensity. Technological dynamism and competitive intensity have a moderating effect on the relationship between collaboration and organisational performance.
4	Behl (2022)	<i>Management Decision</i>	Antecedents to firm performance and competitiveness using the lens of Big Data analytics: a cross-cultural study	To understand how BDACs of tech startups help them gain competitive advantage and improve their firm performance	DCV	Prior studies do not present a growth trajectory for each firm or any specific sector	BDA applications → Firm performance BDA applications → Competitive advantage Moderators: Organisational culture, innovation Competitive advantage → Firm performance	502 tech start-up companies (269 from India, 233 from China)	Machine learning and deep learning (Big data analytics)	Empirical – survey	BDACs positively and significantly impact firm performance and the competitive advantage of tech startups. While organisational culture proved to have a positive impact as a moderator, innovation was found to have a non-significant effect. The results also found a non-significant effect on the firm's age, while its country of origin plays a

											vital role in defining its success.
5	Benassi <i>et al.</i> (2022)	<i>Industrial and Corporate Change</i>	Patenting in 4IR technologies and firm performance	To test the relationships between the accumulated stock of technological knowledge with the Fourth Industrial Revolution and firm performance	N/A	The recent literature mainly focuses on the potential technological disruption of 4IR and future outcomes for employment or tests specific 4IR technologies. Still, there is a lack of studies focusing on the managerial implications of 4IR.	Firm technological capabilities → Firm performance (productivity and profitability)	Longitudinal data set from 491 firms with two datasets, European patent office (EPO) from 2009-2014, and their patent stocks from 1985 onward, as well as EPO2020	Machine learning and deep learning (big data analytical)	Empirical - longitudinal data	The firms' stocks of 4IR patents and labour and total factor productivity have a significant positive relationship 4IR patent filings are more valuable compared with the development of 4IR technological capabilities Firm profitability is not significantly linked to the stock of 4IR patents Productivity has a positive relationship with 4IR-related wireless technology and for AI, cognitive computing and BDA
6	Bhatti <i>et al.</i> (2022)	<i>Annals of Operations Research</i>	Big data analytic capabilities and MSME innovation and performance: a double mediation model of digital platform and network capabilities	To propose a conceptual model that encompasses BDACs, digital platform capabilities and network capabilities, supply chain innovation, and firm performance	DCT and RBV	Although digital platform capabilities have become an essential part of operations and IT research, researchers have recently highlighted the lack of studies that explore the role of different digital capabilities, especially their	BDACs → Digital platform capabilities BDACs → Network capabilities BDACs → Supply chain innovation (SCI) Mediators: Digital platform capabilities, network capabilities BDACs → Firm performance Mediators: Digital platform capabilities, network capabilities SCI → Financial performance BDACs → MSME performance sequentially Mediators: Digital platform capabilities and	300 Top and middle-tier managers of MSMEs in Pakistan	Machine learning and deep learning (big data analytical)	Empirical -survey	BDACs significantly improved platform and networking capabilities. BDACs also improved supply chain innovation and, thus, financial performance. Networking capabilities mediated the relationships of both (a) BDACs–supply chain innovation and (b) BDACs–financial performance

						direct or indirect effects on performance outcomes	SCI BDACs → MSME performance sequentially Mediators: Network capabilities, SCI				
7	Bian and Bian (2022)	<i>Mobile Information Systems</i>	Construction of application model of accounting framework for industry-finance integration management under the background of multimedia technology	To build a management accounting framework in several aspects such as data sources, data overall management, data mining and data processing to make the platform more reasonable and efficient	Fuzzy theory	The previous research does not solve the technical construction of multimedia technology.	N/A	Accounting management system	Machine learning and deep learning, expert system	Empirical - experiment	The optimisation and adjustment control model of the management accounting model used in this paper has played a positive role in the economic benefits based on the financial scheme.
8	Chatterjee et al. (2022)	<i>Journal of Business Research</i>	AI and digitalisation in relationship management: Impact of adopting AI-embedded CRM system	To determine the impact of adopting an AI-embedded customer relationship management system for B2B relationship management	Customer relationship management (CRM)	AI is an emerging technology. Its integration with CRM in the B2B context might pose problems for the employees of the organisations to adapt to AI-CRM technology quickly	N/A	312 responses from 14 firms in the B2B context	Natural language processing (NLP) technology, machine learning	Empirical – survey	This study has focused on how adopting an AI-integrated CRM system in the B2B context can influence firm performance. This study has developed a model (AI-CRM) based on this concept.
9	Chatterjee et al. (2022)	<i>Information Systems Frontiers</i>	Adoption of artificial intelligence and cutting-edge technologies for production system sustainability: a moderator-mediati on analysis	Adopting IoT technology positively impacts the sustainability of a firm's production system.	DCV	Little is known regarding how AI integrated with other cutting-edge technologies could improve operational activities as well as production	BDA, AI, quantum computing, blockchain and digital twins (IoT technology) → Production system sustainability Moderator: Technology turbulence Production system sustainability → Firm performance Mediator: Operational sustainability	412 responses from various manufacturing firms in India	Machine learning and deep learning (big data analytical), Quantum computing	Empirical – survey	Technology turbulence could negatively impact the adoption of these technologies and adversely impact the sustainability of the firm's production system. The present study has demonstrated that the role

						management systems					of technological turbulence as a moderator could impact the relationships between the sustainability of the production system with BDA, AI, quantum computing, blockchain and digital twins (IoT technology)
10	Chowdhury et al. (2022a)	Journal of Business Research	AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework	To examine the relationships between knowledge sharing, employees' AI skills, trust and role clarity in a collaborative working environment to enhance business performance	KBV, socio-technical systems (STS) and organisational socialisation framework (OSF)	The use of AI algorithms and systems is gaining momentum in this industry, e.g. generating paintings, melodies, lyrics, movie scripts and poetry. It is anticipated that the evolution of AI systems will become more sophisticated to address human concerns	Knowledge sharing → AI understanding Knowledge sharing → AI skills Knowledge sharing → AI job clarity Knowledge sharing → Dynamic capability Mediators: AI skills, AI understanding AI understanding → AI job clarity AI understanding → AI trust AI understanding → Dynamic capability AI skills → AI systems AI skills → Dynamic capability AI job clarity → AI trust AI trust → Business performance AI skills → Business performance AI job clarity → Business performance Dynamic capability → business performance AI skills → Business performance Mediator: Dynamic capability AI job clarity → Business performance Mediator: AI trust	164 employees in the UK creative industries	/	Empirical – survey	This study found that AI skills, job clarity, trust and dynamic capability stemming from collaborative intelligence will positively impact business performance.
11	Dadhich and Hiran (2022)	Journal of Cleaner Production	An empirical investigation of extended TOE model on	To investigate how corporate environmental sustainability	TOE framework and TBL approach (a three-part	The primary issues are a lack of awareness, financial resources,	Technological factors → Corporate environmental sustainability (CES) Organisational factors → CES. Value created by economic factors → CES	390 respondents from SMEs	Machine learning and deep learning (big data analytical),	Empirical – survey	Corporate environmental sustainability plays a significant role in shaping the relationships between

			corporate environment Sustainability and dimensions of the operating performance of SMEs: a high order PLS-ANN approach	affects various aspects of a company's performance	accounting framework (social, environmental, and financial))	competition and government assistance.	Worth created by social factors → CES TOES (technological, organisational, economic and social) → Operating performance Mediator: corporate environmental sustainability				technological, organisational, environmental and social factors and SMEs' operating performance.
12	Dondapati <i>et al.</i> (2022)	<i>Materials Today: Proceedings</i>	An integrated artificial intelligence framework for knowledge production and B2B marketing rational analysis for enhancing business performance	To analyse the AI framework and its impact on the business performance of companies	N/A	N/A	AI and B2B marketing → Business performance Mediators: Customer service, marketing, supply chain management, operations, quality of products	/	/	Exploratory – secondary	The usage of AI impacts not only international companies but also domestic companies.
13	Guo <i>et al.</i> (2023)	<i>Personal and Ubiquitous Computing</i>	Can digital transformation of the enterprise break the monopoly?	To test the role of digital transformation in breaking industry and regional monopolies	N/A	The potential economic effect and outcomes of enterprise digital transformation on the enterprise itself, industry development, and economic operation have become essential topics of concern for governments and scholars.	Corporate digital transformation → Performance Corporate digital transformation → Innovation input output of enterprises via the innovation effect → Corporate performance Facilitates the leapfrog development of enterprises	data of management discussion and analysis of word frequencies of Chinese listed companies from 2009 to 2019 in breaking industry and regional monopolies	/	Empirical - longitudinal data	Corporate digital transformation enhances firm performance significantly and could be valuable for breaking industry and regional monopolies Corporate digital transformation improves enterprises' innovation input and output via the innovation effect, consequently improving corporate performance and significantly facilitating enterprises' leapfrog development.

14	Ho <i>et al.</i> (2022)	<i>Journal of Risk and Financial Management</i>	Artificial intelligence and firm performance: does machine intelligence shield firms from risks?	To examine how machine intelligence shields firms from risks in 4 months.	BDA applications	The COVID-19 pandemic changed how firms operated under new social norms and amplified the importance of AI applications.	AI stock market → Conventional stock market COVID-19 pandemic → Stock market performance AI stock market → Conventional stock market in the COVID-19 period	The single-group Interrupted Time-Series Analyses (ITSA) with panel data were used with four interventions: when the news of COVID-19 spread, and the pandemic entered the first, second, third, and fourth months (24 February 2020, 23 March 2020, 20 April 2020, and 18 May 2020, respectively	Machine learning	Empirical – panel date	In the first month of the pandemic, COVID-19's negative impact on the AI stock market was less severe than on the conventional stock market. When the pandemic entered its third month, the performance of the AI stock market recovered more quickly than that of the conventional stock market.
15	Huang <i>et al.</i> (2022)	<i>Information Processing and Management</i>	The business intelligence impact on the financial performance of start-ups	To investigate the influence of business Intelligence on the financial performance of start-ups	N/A	It is valuable to understand the influence of business intelligence on improving individuals' learning and innovation capabilities in a start-up business, which consequently influences its financial performance.	Business Intelligence → Financial performance Business Intelligence → Innovation Business Intelligence → Network learning Innovation → Financial performance Network learning → Financial performance	CEOs and subject matter experts of startup firms were included in the study's statistical population, a sample of 250 people, and a 43-item questionnaire.	Machine learning algorithms and data analytics techniques	Empirical –survey	Business intelligence has a positive impact on innovativeness and network learning and, consequently an impact on financial performance.
16	Huang <i>et al.</i> (2022)	<i>Frontiers in Psychology</i>	The effect of big data analytics capability on competitive performance: the mediating role of resource optimisation and	To determine whether there is a discernible difference between the effects of implementing ERP systems on overall IS/IT	RBV and BDACs	Researchers neglect the fact that a particular enterprise consists of a series of unique resources, and their competitive performance	BDACs → competitive performance Mediators: Resource bricolage, resource optimisation BDA technology capability → Resource optimisation BDA technology capability → Resource bricolage BDA management capability → Resource	242 data was collected from Chinese enterprises	Machine learning algorithms and data analytics techniques	Empirical –survey	Resource bricolage plays a significant mediating role in the relationships between BDA management capability and competitive performance, as well as in the relationship between BDA technology capability and

			resource bricolage	costs, the percentage of costs attributable to IT and other departments, efficiency as profitability, effectiveness as productivity, and the availability of IS/IT services		largely depends on efficient integration and utilisation of resources	optimisation BDA management capability → Resource bricolage				competitive performance. The mediating effect in the former relationship is stronger than in the latter. BDA technology capability only has a direct effect on resource bricolage, while BDA management capability has a more substantial effect on resource optimisation than that on resource bricolage Resource bricolage has a more substantial impact on competitive performance than resource optimisation.
17	Ismail and Muhammad (2022)	<i>International Journal of Sustainable Construction Engineering and Technology</i>	Artificial Intelligence innovation-related factors affecting organisational performance	To present the development of a PLS SEM model of AI-related innovations factors that affect organisational performance	Organisational resources	Lacking a deep knowledge of organisational innovation does not help organisations work in a new, complex environment	Process innovation → Organisation performance Management capabilities → Organisation performance Personal expertise → Organisation performance Organisation structure → Organisation performance	384 respondents are employees from three government organisations in Dubai, which are Dubai Police, Dubai Electricity & Water Authority Dewa, and Emirates Integrated Telecommunications Company.		Empirical –survey	The application of AI innovation improves organisational performance The significant relationships are organisation structure, personal expertise and process innovation The insignificant relationship is management capabilities affecting organisational performance
18	Jaber and Abbad (2022)	<i>Journal of Computer Information Systems</i>	<i>Big Data and Firm Performance: An Outside-in Approach</i>	<i>To investigate whether an outside-in customer relationship management linking capabilities can leverage BDA</i>	RBV, DCV and KBV	Such evidence suggests that firms can still not reap the benefits of this resource. Research has yet to examine how BDA interacts with marketing	Big Data analytics is a combination of data, technology and human skills → CRM linking capabilities Market information processing is a combination of customer-focus and inter-functional cooperation for knowledge interpretation → CRM linking capabilities CRM linking capabilities → Business	315 employees in Jordanian companies	Machine learning algorithms and data analytics techniques	Empirical –survey	BDA presented through the amalgamation of data, technology, and human skills has a positive impact on CRM linking capabilities Market information processing capabilities combining customer focus

				and organisational resources to improve firm performance.		resources broadly and customer relationship management (CRM) specifically to enhance business performance	performance (financial, customer, internal business processes)				and inter-functional coordination for knowledge interpretation also positively affect CRM linking capabilities. CRM linking consequently has a positive impact on multi-dimensional firm performance
19	Jang <i>et al.</i> (2022)	Management Decision	Are smart manufacturing systems beneficial for all SMEs? Evidence from Korea	To investigate the influence of smart manufacturing systems' maturity levels on the performance of SMEs, as well as industry types (high- and low-tech) and human-resource factors (the proportion of production workers) as contingency factors influence the effects of smart manufacturing systems	RBV and contingency theory	The benefits of digitalisation and the impact on performance are unclear	Higher and lower maturity levels of smart manufacturing systems → Financial performance Operational efficiency Moderators: Firms' industry types (high-tech and low-tech industry) and the proportion of production workers (higher and lower)	A sample of 163 Korean manufacturing SMEs	Smart manufacturing systems	Empirical –survey	The higher the maturity levels of smart manufacturing systems, the higher the financial performance and operational efficiency The effect of smart manufacturing systems' maturity levels on financial performance and operational efficiency depends on firms' industry types and the proportion of production workers.
20	Karaboga <i>et al.</i> (2022)	Review of Managerial Science	Big data analytics management capability and firm performance: the mediating role of data-driven culture	To investigate the mediating effect of a data-driven culture on the relationship between Big Data analytics management	DCV	There is little research on how firms should be organised to gain business value from Big Data initiatives and the interaction of third	BDAMC → BDA on operational performance BDAMC → BDA on financial performance BDAMC → Data-driven culture	From 432 prominent data experts across 132 firms operating in Turkey	Machine learning algorithms and data analytics techniques	Empirical - survey	BDAMC is a significant predictor of operational performance, financial performance, and data-driven culture (DDC). In addition, the study's findings confirmed that DDC is both a significant

				capability (BDAMC) and firm performance (i.e. operational and financial performance)		variables that enhance performance outcomes.					predictor and mediator of operational and financial performance.
21	Lee <i>et al.</i> (2022)	Technovation	When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy	To examine how high-tech venture performance varies with AI adoption intensity	Absorptive capacity	The lack of data is a significant constraint in the literature, and hence, many studies have focused on AI's conceptual implications Given that complementary assets are critical to adopting and leveraging new technologies, less is known about how these complementary assets affect the relationship between the AI adoption of high-tech ventures and their performance	AI adoption → Firm performance The rate of AI adoption → Firm performance occurs with some delay AI adoption → Firm productivity is more robust when firms invest in complementary technologies, especially technologies related to Big Data processing and high-power computing AI adoption → Firm productivity is more robust when a firm pursues an internal R&D strategy	300 responses from Korean start-up high-tech ventures	/	Empirical - survey	Performance gains from adoption are more significant among firms that invest in complementary technologies such as cloud computing and database systems. The positive relationship between AI adoption intensity and revenue growth is stronger among firms that pursue a more exclusive R&D strategy specific to the venture.
22	Lei <i>et al.</i> (2022)	Information Processing and Management	Developing an intelligent information system for financial analysis depends on	To develop an intelligent information system for financial analysis	Machine learning theory	Deep neural networks, reinforcement learning and other fast-growing domains have	Ministries / Institutions' reporting of the level of financial → Organisational performance	/	Machine learning algorithms	/	The higher the quality of financial reporting, the better a ministry's or agency's organisational effectiveness

			supervised machine learning algorithms.			scratched the surface, and many applications remain unexplored.					
23	Lin <i>et al.</i> (2022)	<i>Sustainability</i>	Exploring the relationship between abusive management, self-efficacy and organisational performance in the context of human-machine interaction technology and artificial intelligence with the effect of ergonomics	To explore the influence of abusive management and self-efficacy on corporate performance in the context of artificial intelligence-based human-machine interaction technology in enterprise performance evaluation	Organisational psychology	It is essential to develop an environment that we can define as a humane working environment through ergonomics	Human-machine interface → verbal instructions of the employees Employees' perceptions of leaders' abusive management and self-efficacy → Job performance Control variables: age and education level	578 participants in selected international companies in Turkey, Taiwan, Japan, and China	/	Empirical - survey	The human-machine interface can log in based on correct verbal instructions from the employees. In terms of age and education level variables, employees' perceptions of leaders' abusive management and self-efficacy are significantly different from their job performance, respectively.
24	Liu <i>et al.</i> (2022)	<i>International Journal of Environmental Research and Public Health</i>	Can artificial intelligence improve the energy efficiency of manufacturing companies? Evidence from China	To study the impact of AI on the energy efficiency of manufacturing enterprises	Disruptive energy efficiency	The contradiction between economic development and limited energy supply has become increasingly prominent.	AI → Energy efficiency AI → Energy efficiency by promoting technological progress and technical efficiency Moderators: the age of the manufacturing enterprises, manufacturing enterprises' performance	/	/	Empirical – panel data	AI, as measured by the use of industrial robots, has significantly improved the energy efficiency of manufacturing enterprises. The mechanism test shows that AI mainly promotes energy efficiency improvement by promoting technological progress; its impact on technological efficiency is not significant. Heterogeneity analysis shows that the age of the manufacturing enterprises inhibits AI's promoting

											effect on energy efficiency; manufacturing enterprises' performance can enhance AI's promoting effect on energy efficiency, but this promoting effect can only be shown when the enterprise performance is positive.
25	Mishra <i>et al.</i> (2022)	<i>Journal of the Academy of Marketing Science</i>	Artificial intelligence focus and firm performance	To examine the link between firms' focus on AI in their 10-K reports and their gross and net operating efficiency in marketing	Economic and marketing theory	Although of unparalleled significance to firms' future competitiveness, AI adoption represents a substantial and costly challenge for firms, one where the impact of effort is equivocal.	AI focus → Gross operating efficiency AI focus → Return on sales AI focus → Return on marketing-related investment AI focus → Net operating efficiency	Data was collected from two different sources: EDGAR and COMPUSTAT		Empirical – panel data	AI focus positively impacts net profitability, net operating efficiency, and return on marketing-related investment, while AI reduces ad spending and job creation. Finding AI reduction in gross operating efficiency and an increase in net operating efficiency
26	Mohammadnazari <i>et al.</i> (2022)	<i>Environment, Development and Sustainability</i>	A hybrid novel approach for evaluation of resiliency and sustainability in a construction environment using data envelopment analysis, principal component analysis and mathematical formulation	To compare and highlight the importance of three categories (balanced scorecard, resilience engineering and sustainability) on organisational performance. After identifying the shaping factors and assessing the organisation's	Resilience theory	Using only mathematical formulas provides a planning method for organisations that can provide management with medium-term plans.	Balanced scorecard and resilience engineering factors (flexibility, management commitment, reporting culture, learning, awareness, preparedness, teamwork, redundancy, self-organisation, and fault tolerance) → Organisational sustainability performance.	/	/	Empirical - case study	Resilience engineering factors, including flexibility, management commitment, reporting culture, learning, awareness, preparedness, teamwork, redundancy, self-organisation and fault tolerance, positively impact organisational efficiency.

				situation, an artificial neural network (ANN) is applied to help us find the success factor (utility) of future projects							
27	Mustapha (2022)	Sustainability	The UAE employees' perceptions towards factors for sustaining big data implementation and continuous impact on their organisation's performance	To explore the perceptions of UAE employees on factors needed to implement sustainable Big Data and the continuous impact on their organisational performance	Technology adoption model, TOE framework and UTAUT	Some research has investigated critical factors in implementing Big Data initiatives; there is less evidence of research on the perceptions of employees from the organisations adopting Big Data. Very little research has explored critical success factors for the continued success of Big Data in organisations.	Big Data Infrastructure Quality → The long-term sustainable implementation of Big Data applications Moderator: Human cognitive factors Organisational readiness → The long-term sustainable implementation of Big Data applications Moderator: Human cognitive factors Human cognitive factors → The long-term sustainable implementation of Big Data applications Sustainable implementation of Big Data → Business performance	257 employees in Dubai	Machine learning algorithms and data analytics techniques	Empirical - survey	Employees believe that Big Data's sustainable implementation enhances business performance. Employees consider factors such as Big Data architecture quality, human cognitive factors, and organisational readiness to impact sustainable implementation positively. A moderating impact of human cognitive factors was found on the relationship between Big Data architecture quality and sustainable implementation.
28	Niaz et al. (2022)	International Journal of Innovation Management	Capabilities pathway to firm performance: moderating role of environmental dynamism in the food manufacturing firms of Pakistan	To examine the significant influence of entrepreneurial orientation, BDACs and AICs on the firm performance of manufacturing industries of	DCT and contingency theory	Few research studies have looked into the impact of AICs on the service invention process, such as service design and commercialisation	Entrepreneurial orientation (EO) → BDACs EO → AICs EO → Firm performance BDACs → Firm performance AIC → Firm performance Moderator: Environmental dynamism	240 respondents were collected from the survey of Pakistani food manufacturing firms	/	Empirical - survey	EO, BDA and AICs are positively related to firm performance.

				Pakistan using environmental dynamism as a moderator							
29	Olan et al. (2022)	Journal of Business Research	Artificial intelligence and knowledge sharing: contributing factors to organisational performance	To identify redundancies within business processes and offer optimal resource utilisation for improved performance.	N/A	AI needs an enabling intelligent systems environment to grow and engage with the reality of existing challenges in an organisation.	N/A	/	/	Perspective paper	AI technologies alone are not sufficient to improve organisational performance.
30	Pap et al. (2022)	Algorithms	Correlation analysis of factors affecting firm performance and employees wellbeing: application of advanced machine learning analysis	To determine the most critical intra- and extra-organisational elements in assessing the performance of firms using the European Company Survey (ECS)	Machine learning theory and ECS (2019) conceptual framework	N/A	N/A	European Company Survey (ECS) 2019 framework	Machine Learning	Empirical – secondary data	“Skills requirements and skill matching” and “employee voice” are the factors that matter most in enhancing firm performance and well-being.
31	Rakic et al. (2022)	Inzinerine Ekonomika	Digital servitisation and firm performance: technology intensity approach	To investigate the impact of digital servitisation on manufacturing firm performance and demonstrate the role of technology intensity	Servitisation paradox	The technology level of firms is still neglected in the use of digital servitisation, and the neglect of technological intensity is proven as a literature gap in the theory of digital servitisation	Product-related services → Firm performance with low technological intensity Product-related services → Firm performance with medium-low technological intensity Product-related services → Firms' performance with medium-high technological intensity Digital solutions, along with product-related services → Firm performance with low technological intensity Digital solutions, along with product-related services → firm performance with	240 manufacturing firms from the Republic of Serbia	Machine Learning - Big Data Analysis	Empirical - survey	The impact of digital servitisation is more significant with the higher technology intensity level of the industry sector.

							medium-low technological intensity Digital solutions, along with product-related services → firm performance with medium-high and high technological intensity				
32	Rammer <i>et al.</i> (2022)	<i>Research Policy</i>	Artificial intelligence and industrial innovation: evidence from German firm-level data	To examine the role of different AI methods and application areas in innovation	N/A	There are several challenges when it comes to fully utilising the innovative potential of AI.	AI → Innovation performance	/	/	Conceptual	Firms that apply AI broadly (using different methods for different application areas) and that already have several years of experience in using AI obtain significantly higher innovation results
33	Shahzad <i>et al.</i> (2022)	<i>Frontiers in Environmental Science</i>	Decoupling institutional pressure on green supply chain management efforts to boost organisational performance: moderating impact of big data analytics capabilities	To empirically examine the impact of institutional pressure on green supply chain management (GSCM) efforts and the moderating role of BDACs on organisational performance.	RBV	The impact of BDACs on GSCM and environmental performance decision-making processes is not entrenched in the literature.	Coercive pressure → Green supply chain management (GSCM) efforts Normative pressure → GSCM efforts Mimetic pressure → GSCM efforts GSCM → Operational performance GSCM → Environmental performance Moderator: BDACs Operational performance → Environmental performance	This article is based on structured questionnaire data from 347 supply chain personnel.	Machine Learning - Big data analytics	Empirical - survey	GSCM efforts mean organisations can improve operational and environmental performance
34	Song <i>et al.</i> (2022)	<i>Information Systems Frontiers</i>	The source of SMEs' competitive performance in COVID-19: matching big data analytics capability to business models	To examine how BDACs influence SMEs' competitive performance via the mediating role of business models	RBV	Some studies reveal that a large number of firms (more than 60%) fail to improve performance through Big Data, and sometimes, they fall into a	BDA technology capability → Infrastructure attribute of business models (BMs) BDA technology capability → Value attribute of BMs BDA management capability → Infrastructure attribute of BMs BDA management capability → Value attribute of BMs Infrastructure attribute of BMs → Growth	242 SMEs in China	Machine Learning - Big data analytics	Empirical - survey	Infrastructure and the value attributes of BMs play a mediating role in enhancing the relationship of BDACs on competitive performance, and an improvement in financial performance comes from the matching of BDA

						survival crisis due to investments in BDACs projects. This so-called “IT productive paradox” drives scholars to urgently explore the impacting mechanism of BDACs on firms’ competitive performance.	performance Infrastructure attribute of BMs → Financial performance. Value attribute of BMs → Growth performance Value attribute of BMs → Financial performance Moderator: COVID-19				management capability with the infrastructure attributes of BMs COVID-19 has a positive moderating effect on the relationship between BDA management capability and the value attributes of BMs
35	Su <i>et al.</i> (2022)	<i>European Journal of Innovation</i>	Big data analytics capabilities and organisational performance: The mediating effect of dual innovations	To investigate the impact of BDACs on organisational performance through the mediating role of dual innovations	RBV	There is a need to understand the mechanism by which data-based insights are transformed into actions and business value	BDACs (tangible, human skills, intangible resources) → Dual innovation Organisational performance BDACs (tangible, human skills, intangible resources) → Dual innovation → Organisational performance	From 309 respondents working in Chinese manufacturing enterprises	Machine Learning - Big data analytics	Empirical - survey	There is a direct and indirect effect of BDACs on organisational performance. Dual innovations positively mediate BDACs’ effect on organisational performance.
36	Wamba (2022)	<i>International Journal of Information Management</i>	Impact of artificial intelligence assimilation on firm performance: The mediating effects of organisational agility and customer agility	To investigate the impacts of AI assimilation on firm performance and assess the mediating effects of organisational agility and customer agility on the relationship	DCV	The literature lacks empirical studies on how AI assimilation could improve organizational outcomes such as organisational agility, customer agility, and firm performance.	AI assimilation → Organisational agility AI assimilation → Customer agility Organisational agility → Customer agility AI assimilation → Firm performance Organisational agility → Firm performance Customer agility → Firm performance AI assimilation → Firm performance Mediators: organisational agility and customer agility	From 205 supply chain executives in the USA /		Empirical - survey	AI assimilation is an essential predictor of firm performance, customer agility and organisational agility, with more potent effects on the latter. Organisational agility is a vital predictor of customer agility and firm performance, with more substantial effects on the former. Furthermore, customer and organisational agility are complementary partial

											mediators of the relationship between AI assimilation and firm performance.
37	Wang (2022)	Systems Research and Behavioral Science	AI-enabled IT capability and organisational performance	To examine information technology, the impact of AI on budget management and organisational performance	DCT	The government and enterprises attach great importance to applying AI-enabled IT capability in budget management	IT essential capability → Organisational performance IT system practice → Organisational performance IT essential capability → Capital budget IT essential ability → Financial budget IT system practices → Capital budget IT system practices → Financial budget Capital budget → Organisational performance Financial budget → Organisational performance	256 responses from high-tech enterprises in China	AI-enabled IT system	Empirical - survey	AI has a positive impact on organisational performance Applying AI in capital budgeting and financial budgeting is effective in a changeable environment
38	Wang and Han (2022)	Security and Communication Networks	A prediction and evaluation model analysis of enterprise economic management mode based on neural network strategy	To predict future trends in enterprise performance management	Neural networks	There are still some problems with company performance management, and not enough attention is paid to applying management accounting in performance management.	BP neural network without LSTM → Business performance management BP neural network with LSTM layer → Business performance management	/	Neural network	Qualitative	AI technology has a positive impact on corporate management performance Two types of neural networks are used: the single BP neural network without LSTM and the BP neural network with LSTM layer, which is used to capture the corporate time characteristics of performance between the cost-savings ratio and corporate performance
39	Wang <i>et al.</i> (2022)	Information Processing and Management	Business intelligence ability to enhance organisational performance and performance	To determine how the quality of systems and intelligent business capabilities	N/A	“Exogenously fixed” or non-discretionary factors should occur beyond the authority of DMU	Integration of business intelligence infrastructure → Business intelligence capabilities Business intelligence capability → Business intelligence reliability	managers of 50 selected private companies that use the <u>business intelligence</u> system	Business intelligence	Empirical - Survey and field experiment	Business intelligence increases performance, which is positively related to competitive advantage and increases the organisation's competitive

			evaluation capabilities by improving data mining systems for competitive advantage	improve the various dimensions of performance appraisal capabilities		management and need further study	Integrating business intelligence infrastructures → Business intelligence reliability Integration of business intelligence infrastructure → Performance appraisal capabilities Business intelligence capabilities → Performance appraisal capabilities Business intelligence reliability → Performance appraisal capabilities Performance appraisal capabilities → Competitive advantage				advantage. The integration of business intelligence infrastructure impacts business intelligence capabilities.
40	Waqas and Tan (2022)	<i>Environmental Science and Pollution Research</i>	Big data analytics capabilities for reinforcing green production and sustainable firm performance: the moderating role of corporate reputation and supply chain innovativeness	To examine the role of BDA-technology capability, green technological innovation capabilities (GTICs), and environmental orientation toward green production and sustainable firm performance and the mediating role of green production and green competitive advantage and the moderating role of corporate reputation and supply chain innovativeness	DCT and RBV	Organisational capabilities are not only built by BDA, predictive analytics and GTIC, but other factors such as supply chain innovativeness, sustainability, green production, and supply chain competitiveness can also play a significant role.	BDA technology capability → Green production Green technological innovation capability → Green production Environmental orientation → Green production Green production → Green competitive advantage Green competitive advantage → Sustainable firm performance BDA technology capability → Competitive advantage Mediators: Green production, green competitive advantage Moderators: Corporate reputation, supply chain innovativeness	A total of 192 Pakistani manufacturing firms	Machine Learning - Big data analytics	Empirical - Survey	BDA technology capability, green technical innovation and environmental orientation positively contribute to green production. Moreover, green production helps achieve a green competitive advantage, positively influencing sustainable firm performance. The mediating roles of green production and green competitive advantage, as well as the moderating role of corporate reputation and supply chain innovativeness, were also confirmed.

41	Wijayati <i>et al.</i> (2022)	<i>International Journal of Manpower</i>	A study of artificial intelligence on employee performance and work engagement: the moderating role of change leadership	To explore employee perceptions of companies engaged in services and banking of the role of change leadership on the application of AI that will impact the performance and work engagement in conditions that are experiencing rapid changes	DCV	AI has drawn controversy among both practitioners and academics	AI → Employee performance and work engagement. Moderator: Change leadership	254 respondents are employees of companies engaged in the services and banking sector in the East Java, Indonesia region	/	Empirical - Survey	AI has a significant positive effect on employee performance and work engagement. Change leadership positively moderates the influence of AI on employee performance and work engagement.
42	Wu and Monfort (2022)	<i>Psychology and Marketing</i>	Role of artificial intelligence in marketing strategies and performance	To examine the role of AI as a marketing strategy and explain its contribution to firms and the factors influencing their development	RBV	There are many unanswered questions regarding the potential for AI to be successful in influencing strategy choice and performance Some marketing problems within AI strategic decisions are ill-defined or under-structured The literature on AI in marketing applications remains fragmented	Market orientation → Organisational performance AI marketing strategy → Performance Marketing capabilities → Marketing strategy Marketing capabilities → Organisational performance Customer value co-creation → AI marketing strategy Customer value co-creation → Performance	278 participants from 842 food firms in Taiwan	/	Empirical - Survey	The implementation of an AI marketing strategy affects performance Marketing capabilities, customer value co-creation and market orientation are positively related to performance Causal conditions of marketing capabilities, customer value co-creation, market orientation and AI marketing strategies improve firm performance

43	Xie <i>et al.</i> (2022)	<i>Journal of Global Information Management (JGIM)</i>	Big Data analytics capability and business alignment for organisational agility: a fit perspective	To investigate the impact of BDACs on organisational agility under the moderating effect of BDACs–business alignment and its impact on performance through organisational agility	BDACs and source-position-performance framework	Not all firms improve agility and performance after investing in BDA	BDACs → Market responsiveness agility and operational adjustment agility Moderators: BDACs–strategy alignment, BDAC–operations alignment Market responsiveness agility → Market performance, financial performance, operational performance Operational adjustment agility → Market performance, financial performance, operational performance.	Data from a matched-pair survey of business, data technology, and financial executives in 161 organisations were used.	Machine Learning - Big data analytics	Empirical - survey	Organisational agility plays a positive mediating role in the relationship between BDACs and organisational performance, except that the mediating effect of operational adjustment agility on BDACs and market performance is not statistically significant.
44	Yu <i>et al.</i> (2022)	<i>Business Strategy and the Environment</i>	Circular economy practices and industry 4.0 technologies: a strategic move of the automobile industry (20)	To examine the role of industry 4.0 on circular economy practices and supply chain capability to improve firm performance	Machine learning theory	The contemporary research on the adoption of industry 4.0 technologies lacks empirical findings in circular economy business models	Industry 4.0 technologies → Circular economy practices Industry 4.0 technologies → Supply chain capability Supply chain capability → Circular economy practices SC capability → Operational performance SC capability → Economic performance Circular economy practices → Operational performance Circular economy practices → economic performance Operational performance → Economic performance	286 respondents in the automobile industry in China /		Empirical – survey	Industry 4.0 plays a positive role in implementing circular economy practices and supply chain capability.
45	Zhang (2022)	<i>Mathematical Problems in Engineering</i>	A neural network model for business performance management based on random matrix theory	To use random matrix theory to construct a neural network model for business performance management	Neural networks	HR performance appraisal systems are not perfect, and the small and medium-sized enterprise mechanism is still relatively prominent	Neural network model → Business performance management	192 data from 48 Internet companies 2019-2022 as training samples, and eight companies used as test samples	N/A	Empirical – panel data	The neural network model positively impacts business performance management based on random matrix theory.

46	Zhou <i>et al.</i> (2022).	<i>Frontiers in Psychology</i>	A study on the cognition and emotion identification of participative budgeting based on artificial intelligence.	To examine the role of cognition and emotion in participative budgeting and corporate performance	Cognitive psychology and organisational behaviour theory	There may be a complex interactive mechanism between participative budgeting and corporate performance	Participative budgeting → Organisation performance Moderators: Cognition ability, emotional intelligence and self-efficacy	345 listed companies in China	AI-based cognition and emotion identification system	Empirical - survey	Human cognition and emotion have a positive moderating effect on the relationship between participative budgeting and corporate performance.
2021											
47	Arefin <i>et al.</i> (2021)	<i>Journal of Knowledge Management</i>	Organisational learning culture and business intelligence systems of health-care organisations in an emerging economy	To test the role of business intelligence systems (BIS) in the link between organisational learning culture and organisational performance in the healthcare setting	Competence-based theory	The critical role of business intelligence systems in the organisational context has not been understood adequately	Organisational learning culture → Organisational performance	217 mid- and top-level administrators of healthcare companies in Bangladesh	Business intelligence systems	Empirical - survey	The organisational learning culture impacts organisational performance within healthcare organisations through BIS.
48	Cappa <i>et al.</i> (2021)	<i>Journal of Innovation Management</i>	Big Data for creating and capturing value in the digitalised environment: unpacking the effects of volume, variety, and veracity on firm performance	To understand when the benefits outweigh the costs	RBV	It is unclear how Big Data impacts long-term firm performance	Big data volume → Firm performance (negatively) Big Data variety moderates impact of Big Data volume on firm performance (positively) Big Data veracity → Firm performance (positively)	Companies among the top-listed firms in the USA, all the mobile applications in the sample are offered for free on the Google Play store	Machine Learning - Big data analytics	Empirical – Netographic	The volume of Big Data has a negative impact on firm performance High values of volume and variety support firms to create value that influences their performance positively High levels of veracity (i.e. a high percentage of employees devoted to Big Data analysis) are related to firms benefiting from Big Data via value capture

49	Dubey <i>et al.</i> (2021)	<i>Industrial Marketing Management</i>	Facilitating artificial intelligence-powered supply chain analytics through alliance management during the pandemic crises in the B2B context	To test the impact of alliance management capability (AMC) and AI on supply chain analytics capability (AI-SCAC) via environmental dynamism	DCV and contingency theory	Even though AMC has a strong influence on SCAC, the evidence for such influence is mostly anecdotal	Alliance management capability (AMC) → AI-driven supply chain analytics (AI-SCAC) AI-SCAC → Operational performance AI-SCAC → Financial performance Moderator: Environmental dynamism AMC → AI-SCAC	26 interviews with senior-level supply chain managers from the auto components manufacturing industry, 167 responses from organisations in the ACAMA database, which contains details of over 800 firms in India and abroad	/	Empirical – interview and survey	Alliance management capability enhances the operational and financial performance of the organisation via AI-powered supply chain analytics capability. Alliance management capability influences AI-powered supply chain analytics capability positively via environmental dynamism.
50	Giap <i>et al.</i> (2021)	<i>Inter. Journal of Advanced Computer Science and Applications</i>	Firm performance prediction for macroeconomic diffusion index using machine learning	To test the achievements of machine learning on firm performance prediction and to propose an emerging idea of applying it to macroeconomic prediction	Micro-, meso-and macro-framework	No study has tested machine learning algorithms to predict firm performance.	N/A	Data was collected in a wide range of enterprise surveys conducted by the General Statistics Office of Vietnam. It includes more than 500,000 companies with nearly 200 variables for each observation.	Machine Learning - Big data analytics	Empirical - Experiment	Firms' performance fluctuates across industries, and it is building a diffusion index that is a potential early warning indicator for macroeconomic management.
51	Jonny and Toshio. (2021)	<i>International Journal of Technology</i>	Building an implementation model of IoT and big data and its improvement	To develop a framework regarding the impact of the IoT and big data implementations on business performance	N/A	There is no framework to understand the impact of IoT and Big Data implementations on business performance	Business process improvement → Business model innovation Marketing strategies Business model innovation Marketing strategies → Business performance.	120 valid responses from the manufacturing industry	Machine Learning - Big data analytics	Empirical - survey	Business process improvement significantly influences business model innovation. Business process improvement significantly influences marketing strategies Business model innovation significantly influences business performance Business process improvement significantly

											influences business performance Marketing strategies do not significantly influence business performance
52	Keshavartz <i>et al.</i> (2021)	<i>Sustainability</i>	The value of big data analytics pillars in the telecommunication industry	To look at the BDA technology pillars that might encourage firms to use Big Data technology across a range of industries	RBV	BDA pay off for some firms while failing to pay off for others as investment in Big Data continues to present significant challenges due to the missing link between analytics capabilities and firm performance	N/A	BDA Experts in the telecommunication industry	Machine Learning - Big data analytics	Exploratory – Interviews and case studies	The findings support the crucial components that make the BDAP model sustainable, a critical aspect that significantly impacts business performance.
53	Ma <i>et al.</i> (2021)	<i>Sage Open</i>	Investigating the Impact of information technology, absorptive capacity, and dynamic capabilities on firm performance: an empirical study	To test the impact of IT, absorptive capacity (ACAP) and DCs on firm performance	DC perspective ACAP as a firm KBV	There has been little study on the link between IT and ACAP	Information technology (IT) → Firm absorptive capacity IT→ Firm dynamic capabilities Absorptive capacity →Firm performance Dynamic capabilities→Firm performance Absorptive capacity → Firm dynamic capabilities IT→Firm performance IT→ ACAP →Firm performance	A total of 241 samples were obtained from respondents who represented their firms in China.	Information AI technology	Empirical – survey	IT has a significant impact on absorptive capacity IT has a positive effect on DCs Absorptive capacity has a positive impact on firm performance DCs have a positive impact on firm performance Absorptive capacity has a positive effect on DCs IT has a positive impact on firm performance
54	Mikalef and Gupta (2021)	<i>Information and Management</i>	Artificial intelligence capability: conceptualisation, measurement calibration, and	To define and identify the AI-specific resources that jointly create AICs, measure	RBV	Little research identifies the main components of organisations and conceptually grounded	AICs → Organisational creativity AICs →Organisational performance Organisational creativity → Organisational performance	A sample of 143 senior technology managers who were aware of AI projects in their firms	/	Empirical – survey	AICs enhance organisational creativity and performance.

			empirical study on its impact on organisational creativity and firm performance	firm' AICs and test the relationship between AICs and organisational creativity and performance		knowledge about how to build AICs					
55	Nasrollahi <i>et al.</i> (2021)	<i>Big data and cognitive computing</i>	The impact of Big Data adoption on SMEs' performance	To test the impact of BDA on SMEs' performance	Diffusion of innovation (DOI) theory Institutional theory TOE	There is a lack of empirical research related to Big Data adoption and Big Data business value, particularly in SMEs	Feature factors (FEF) Organisational factors (ORF) Utility factors (UTF) Technological factors (TEF) Stakeholder factors (STF) Financial factors (FIF) Processing factors (PRF) Cultural factors (CUF) Environmental factors (ENF) Managerial factors (MAF) Skill factors (SKF) → Operational performance (OPP) Feature factors (FEF) Organisational factors (ORF) Utility factors (UTF) Technological factors (TEF) Stakeholder factors (STF) Financial factors (FIF) Processing factors (PRF) Cultural factors (CUF) Environmental factors (ENF) Managerial factors (MAF) Skill factors (SKF) → Social performance (SOP) Feature factors (FEF) Organisational factors (ORF) Utility factors (UTF) Technological factors (TEF) Stakeholder factors (STF) Financial factors (FIF) Processing factors (PRF) Cultural factors (CUF) Environmental factors (ENF) Managerial factors (MAF) Skill factors (SKF) → Organisational performance (ORP)	224 managers of Iranian SMEs	/	Empirical -survey	BDA influences twelve elements in SMEs. BDA can affect both operational and economic performance. BDA does not impact the effect of economic performance on social performance
56	Obitade (2021)	<i>Journal of Decision Systems</i>	The mediating role of knowledge management and information	To examine the relationship between a company's	Organisational learning theory and strategic decision-making	There is a general lack of understanding of the mechanisms	Knowledge management capabilities → Systems selection decision System selection decisions: Emerging BDA criteria	From a cross-sectional survey of 523 IT professionals in the US, UK, and India	Information system	Empirical -survey	The information systems selection process, enhanced by knowledge management capabilities,

			systems selection management capability on Big Data analytics quality and firm performance	knowledge management capabilities, information system selection management capabilities, and BDA quality and business performance	theory	through which organisations derive competitive benefits from BDA	Considered emerging: BDA software vendor criteria, consultants' criteria BDA solution criteria → BDA quality Consultant selection criteria → BDA quality BDA → Firm performance Information systems selection management capability → Organisational competitive position				is positively related to BDA system quality and firm performance. Inconsistently, with prior studies on transactional systems, no support was found for the hypothesis that software vendor criteria influence BDA quality.
57	Pinheiro <i>et al.</i> (2022)	<i>Business Strategy and Environment</i>	Circular economy-based new products and company performance: the role of stakeholders and Industry 4.0 technologies	To test the impact of industry 4.0 technologies on stakeholder pressure, circular product design (CPD) will ultimately influence company performance.	The theory of stakeholders	The concept of the circular economy seems like a vague concept or a new label for old green management practices	Stakeholder pressure → CPD The adoption of Industry 4.0 technologies → CPD CPD → EP of companies CPD → MP of companies EP → MP of companies	Data were obtained from firms developing products in Brazil's electric–electronic equipment (EEE) sectors.	Industry 4.0 technology	Empirical - survey	The application of Industry 4.0 technologies favours CPD, particularly AI and BDA. Pressure from stakeholders can enhance the adoption of circular strategies CE adoption has a positive impact on market performance
58	Tortora <i>et al.</i> (2021)	<i>Journal of Business Research</i>	'I digitise so I exist'. Searching for critical capabilities affecting firms' digital innovation	To investigate whether and how different knowledge-based capabilities contribute to the development of digital innovation via social media	DCT (knowledge-based capabilities) and digital innovation	Limited attention has been paid to the process of generating capabilities support for digital transformation management	Market-sensing capabilities → Digital innovation Knowledge acquisition capabilities → Digital innovation Knowledge generation capabilities → Digital innovation Moderator: Social media usage	A sample of 210 managers operating in Italian firms	Machine Learning - Big data analytics	Empirical - survey	Knowledge acquisition capabilities have a positive impact on digital innovation, while market-sensing capabilities and knowledge generation capabilities have a negative impact on digital innovation. Social media usage has a positive moderating effect on the relationship between knowledge generation capabilities and digital innovation and the relationship between

											knowledge acquisition capabilities and digital innovation.
59	Zhu <i>et al.</i> (2021)	<i>International Journal of Information Management</i>	A longitudinal study of the actual value of big data and analytics: the role of industry environment	To test the impact of BDA implementation on organisational performance and the moderating role of industry characteristics on BDA-performance relationships	Organisational learning theory	There has been little empirical longitudinal study of the BDA-BDA-performance relationship.	BDA implementation → Firm performance (Operational efficiency and business growth) Moderator: Industry environment (complexity, dynamism and generosity)	Using secondary data regarding BDA implementation from 2010 to February 2020	/	Empirical – longitudinal	BDA has a positive impact on two components of firm performance: operation efficiency and business growth The influence of BDA on operational efficiency is amplified in less dynamic environments, while the relationship between BDA and business growth is more pronounced.
2020											
60	Erkmen <i>et al.</i> (2020)	<i>Sustainability</i>	The role of innovative climate in the relationship between sustainable IT capability and firm performance	To examine the effects of sustainable IT capability on company performance as well as the moderating role of innovative climate in the three-dimensional construct of IT capability that includes managerial IT competence, technical IT capability and human support	RBV and positioning theory	Some studies have confirmed that IT investments are related to a firm's production, which neglects efficiency expectations.	IT capabilities: (a) technical IT capability, (b) managerial IT capability and (c) human capital support → Qualitative firm performance Moderator: Innovative climate	The data from 221 managers of IT companies listed in the top 500 list of Information and Communication Technologies Authority (ICTA) in Istanbul and Ankara, Turkey, among other places	IT	Empirical - survey	Management and technical IT skills have a significant impact on quantitative firm success. They impact the quantifiable performance of business organisations' tangible outputs. Human capital support does not appear to impact quantitative performance significantly.

61	Ghasemaghaei and Calic (2020)	<i>Journal of Business Research</i>	Assessing the impact of big data on firm innovation performance: big data is not always better data.	To test the influence of Big Data's main characteristics (volume, variety, and velocity) on innovation performance (innovation efficacy and efficiency), which consequently influences firm performance (customer perspective, financial returns and operational excellence)	N/A	There has been little study on the links between Big Data, firm innovation performance and overall firm performance	Data variety → Innovation performance Data volume→ Innovation performance Data velocity → Innovation performance Big Data → Innovation performance → Firm performance	the survey was sent through email to 1286 individuals during two months of April and May 2018 in the US	Machine Learning - Big data analytics	Empirical -survey	Data variety and velocity improve firm innovation performance Data volume has no significant impact on firm innovation performance Data volume does not play an essential role in improving firm innovation performance Data velocity plays a more critical role in enhancing firm innovation performance than other big data characteristics
62	Huang <i>et al.</i> (2022)	<i>Information Systems Frontiers</i>	Initial evidence on the impact of big data implementation on firm performance	To test the relationship between Big Data implementation and the corresponding financial performance, productivity and market value	N/A	Top management must determine whether Big Data implementation actually improves firm performance	Big Data implementations → Financial performance Big Data implementations → Productivity Big Data implementations →Market values Early adopters of Big Data → Financial performance Early adopters of Big Data →Productivity Early adopters of Big Data → Market value	174 firms with big data implementation announcement	Machine Learning - Big data analytics	Empirical -panel	Implementing big Data positively impacts the improvement in financial performance and market value, but this effect is not more substantial for first movers.
63	Maroufkhani <i>et al.</i> (2020)	<i>Journal of Science and Technology</i>	Big data analytics adoption model for small and medium enterprises	To develop a unified model for the adoption of BDA among SMEs based on the TOE model and RBV	TOE model and RBV	Although SMEs are essential for the economy, they lag far behind in BDA use.	Technological context → Adoption of BDA Organisational context →Adoption of BDA Environmental context → Adoption of BDA BDA adoption →Financial performance BDA adoption → Market performance Technological context → Adoption of BDA → Financial performance	112 manufacturing SMEs in Iran	Machine Learning - Big data analytics	Empirical -survey	BDA has a mediating effect on the link between technological, organisational and environmental contexts and SME performance Technological and organisational elements are

						Technological context → BDA adoption → Market performance Organisational context → Adoption of BDA → Financial performance Organisational context → Adoption of BDA → Market performance Environmental context → Adoption of BDA → Financial performance Environmental context → Adoption of BDA → Market performance				the more significant drivers of BDA adoption in the context of SMEs BDA adoption can improve the financial and market performance of SMEs
64	Rahmana and Zhao (2020)	<i>Accounting and Management Information Systems</i>	Information technology capability and firm performance in the era of Big Data analytics: evidence from the United States	An examination of the relationship between BDA and firm performance in the 2010s, the era of IT capability and IT adoption	N/A	Over the years, it has become increasingly important to understand whether firms with solid IT capabilities perform better because of the evolution of business intelligence and the proliferation of analytic tools. Firms that had superior IT capabilities in the 2010s are associated with higher average profit ratios than those of control firms. Firms that had superior IT capabilities in the 2010s are associated with lower average cost ratios than those of control firms. Firms that had superior IT capabilities in the 2010s are associated with higher average profit ratios than those of control firms in all subsequent years. Firms that had superior IT capabilities in the 2010s are associated with lower average cost ratios than those of control firms in all subsequent years. Firms that had superior IT capabilities in the 2010s are associated with higher average profit ratios than those of control firms after adjustment for prior financial performance. Firms that had superior IT capabilities in the 2010s are associated with lower average cost ratios than those of control firms after adjustment for prior financial performance. After adjustment for previous financial performance, firms that had superior IT capabilities in the 2010s are associated with higher average profit ratios than those of	All data are publicly available from Compustat and InformationWeek (IW) 500	Machine Learning - Big data analytics	Empirical – secondary	The sample of US companies showed no significant correlation between IT capability and performance.

							control firms in the subsequent years. After adjustment for previous financial performance, firms that had superior IT capabilities in the 2010s are associated with lower average cost ratios than those of control firms in the subsequent years.				
65	Ramadan <i>et al.</i> (2020)	<i>Applied Sciences-Basel</i>	Sustainable competitive advantage driven by big data analytics and innovation	To test the relationships among BDACs and data availability and innovation capabilities and consequent contribution to the development of a sustainable competitive advantage	DCT	Research on whether BDA and innovation alone can sustain a firm's competitive advantage is lacking	Data availability → BDACs BDACs → Innovation capabilities (ICs) BDACs → Sustainable competitive Advantage ICs → SCA	117 manufacturing companies	Machine Learning - Big data analytics	Empirical -survey	BDACs rely on the level of DA positivity and have an essential role in enhancing innovative capabilities. Innovative capabilities have a positive influence on a firm's sustainable competitive advantage, while BDACs have no direct impact on it.
66	Saïde and Sheng (2020)	<i>Big Data</i>	Toward business process innovation in the big data era: a mediating role of big data knowledge management	To identify whether Big Data and knowledge management can be established in these emerging issues. It used a survey questionnaire to collect data from various firms and industries	Big Data analytics technological (BDAT), knowledge exploration-exploitation capabilities (KEECs) and business process innovation (BPI)	Recent studies of BDA mostly focus on computational aspects such as computational intelligence for a cyber-physical system, machine learning, the IoT and prediction techniques rather than management or managerial contributions in the knowledge management (KM) field and business process innovations in the	BDAT → Knowledge exploration-exploitation capabilities BDAT → Business process innovation	155 companies in a developing country such as Indonesia	Machine Learning - Big data analytics	Empirical -panel	There is a positive relationship between knowledge exploration-exploitation capabilities and business process innovation; Big Data knowledge management successfully mediates the relationship between knowledge exploration-exploitation capabilities and business process innovation.

						KM field					
67	Shabbir and Gardezi (2020)	<i>Journal of Big Data</i>	Application of big data analytics and organisational performance: the mediating role of knowledge management practices	To develop and investigate the link between the application of BDA and organisational performance in SMEs and the mediating role of knowledge management practices.	RBV	There is a lack of understanding of the link between the application of BDA and organisational performance and the role of knowledge management practices	BDA → Organisational performance Application of BDA → Knowledge management practices Knowledge management practices → Organisational performance BDA → Knowledge management practices → Organisational performance	210 respondents from Pakistan encompassed business owners, executives, managers, and other relevant employees who can respond to big data analytics and knowledge management practices.	Machine Learning - Big data analytics	Empirical - survey	The application of BDA has a positive impact on organisational performance and knowledge management practices partially mediate the link between the application of BDA and organisational performance in SMEs
68	Vitari and Raguseo (2020)	<i>International Journal of Production Research</i>	Big data analytics business value and firm performance: linking with environmental context	To test the moderating role of environmental features on the link between BDA business value and firm performance	Contingency theory and RBV	No research tests the role of environmental characteristics in which companies operate	BDA business value → Firm performance (financial performance, market performance and customer satisfaction) Moderators: munificent environments, the dynamism of the environment	a sample of 142 companies	Machine Learning - Big data analytics	Empirical -survey	BDA business value leads to higher firm performance (financial performance, market performance and customer satisfaction) and has a stronger relationship in munificent environments, but the dynamism of the environment has no moderating impact on the performance of BDA solutions
69	Wamba-Taguimdje et al. (2020)	<i>Business Process Management Journal</i>	Influence of artificial intelligence (AI) on Firm Performance: the business value of AI-based transformation	To examine how AI impacts company performance, particularly by leveraging the economic benefits of AI-based	IT capabilities theory	There is a need to understand the impact of AI on firm performance	AI management capabilities → AI capabilities, which are positively associated with the influence of AI at the process level AI personal expertise → AICs, which are positively associated with the influence of AI at the process level AI infrastructure flexibility → AICs, which are positively associated with the influence of AI	A review of 500 case studies from the websites of IBM, AWS, Cloudera, Nvidia, Conversica, Universal Robots, etc	/	Exploratory – secondary data	AI can improve performance at both the organisational (financial, marketing and administrative) and process levels. By building on these AI attributes, organisations can,

			projects	transformation initiatives			at the process level The automation effect → The process level, which is positively associated with the influence of AI at the organisational level The informational effect → The process level, which is positively associated with the influence of AI at the organisational level The transformational effect → The process level, which is positively associated with the influence of AI at the organisational level				therefore, enhance the business value of their transformed projects. Organisations achieve performance through AICs only when they use their features/technologies to reconfigure their processes.
70	Yadav <i>et al.</i> (2020)	<i>The TQM Journal</i>	Impact of Industry4.0/ICTs, Lean Six Sigma and quality management systems on organisational performance	To compare the influence of Industry 4.0 / emerging information and communication technologies (ICTs)	Theory of inventive problem solving	No study compares the difference between management systems, Lean Six Sigma and emerging ICTs	N/A	A total of 105 responses were collected from Indian organisations	Industry 4.0	Empirical -survey	There is a significant difference among 20 organisational performance indicators under different combinations of QMS, LSS and ICTs No significant difference between absenteeism and throughput
71	Yadegaridehkordi, <i>et al.</i> (2020)	<i>Electronic Commerce Research and Applications</i>	The impact of big data on firm performance in the hotel industry	To define the key elements influencing Big Data adoption and its consequent enhance the firm performance	Human-organisational-technology fit TOE framework	Understanding Big Data adoption and firm performance is still in its early stages	Technology (complexity, compatibility, relative advantage, cost of adoption) → Big Data adoption Organisation (management support, organisational resource, organisation size) → Big Data adoption Environment (external pressure, external support, security and privacy concerns) → Big Data adoption Human (change efficacy, IT expertise) → Big Data adoption Big Data adoption → Firm performance	418 responses from top managers and/or owners of Malaysian SMEs hotels	Machine Learning - Big data analytics	Empirical -survey	Relative advantage, management support, IT expertise, and external pressure are the most important factors in the technological, organisational, human, and environmental dimensions, but technology is the most influential dimension.
72	Yang <i>et al.</i> (2020)	<i>Enterprise Information Systems</i>	The influence of intelligent manufacturing on financial performance and	Propensity score matching with difference in differences (PSM-DID)	Disruptive innovation theory	There is still a lack of empirical research on the impact of intelligent	N/A	The enterprise panel data of intelligent manufacturing implemented by China's manufacturing industry	Intelligent manufacturing	Empirical -panel data	The implementation of intelligent manufacturing has a significant role in promoting financial performance and

			innovation performance: the case of China	method to investigate the impact of intelligent manufacturing on financial performance and innovation performance		manufacturing on enterprise performance, especially in China.		from 2014 to 2019			innovation performance. Technology-intensive industries improve the quantity of innovation by implementing intelligent manufacturing, thus promoting the improvement of short-term financial performance, but the improvement of innovation quality has a negative impact on short-term financial performance.
73	Yasmin <i>et al.</i> (2020)	<i>Journal of Business Research</i>	Big data analytics capabilities and firm performance: An integrated MCDM approach	To explore the interdependence of BDACs and their impact on firm performance.	RBV and DCV	Different capabilities to acquire to get ahead in Big Data efforts and whether to acquire technical or non-technical capabilities	BDACs (infrastructure capability, human resource management capability and management capabilities) → Firm performance	data set obtained from 40 selected case study firms in Pakistan	Machine Learning - Big data analytics	Empirical -secondary data	BDACs are interdependent, and infrastructure capabilities are the highest-ranked among all, followed by management and human resource capabilities, respectively. BDACs have a positive impact on firm performance, while more strongly linked to operational performance than to market performance.
2019											
74	Akhtar <i>et al.</i> (2019)	<i>British Journal of Management</i>	Big data-savvy teams' skills, big data-driven actions and business performance	To test the relationship between the use of Big Data-savvy team skills, Big Data-driven actions and	RBV	Existing research does not test the application of cross-functional teams' skills and their relationship to the role of	Big Data-savvy (BDS) team skills → Big Data-driven (BDD) actions BDS teams' skills → Business performance BDD actions → Business performance BDS teams' skills → BDD actions → Business performance	collected from 240 big data experts working in global agrifood networks	Machine Learning - Big data analytics	Empirical -survey	BDS team skills influence Big Data-driven actions and consequently improve business performance, and those firms that focus on such actions perform better compared to those that do

				business performance		data-driven actions and performance					not emphasise it
75	Dubey <i>et al.</i> (2019)	<i>British Journal of Management</i>	Big Data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture	To develop and empirically test a framework that explains the importance of resources for the development of capabilities, skills and Big Data culture and subsequently enhances cost and operational performance	RBV, institutional theory and organisational culture	The important role of external institutional pressures on the resources of the organisation to develop Big Data capability is unclear	Coercive pressures Normative pressures Mimetic pressures → Tangible resources Human skills Tangible resources Human skills → Big Data predictive analytics Moderator: Big Data-driven culture Big Data predictive analytics (BDPA) → Cost performance Operational performance Control variables: Industry Firm size	a sample of 375 manufacturing companies located across India	Machine Learning - Big data analytics	Empirical -survey	Institutional pressures (i.e. coercive, normative and mimetic pressures) have a positive impact on the selection of tangible resources. Normative and mimetic pressures have a positive impact on human skills, while coercive pressures have no significant effect. HR can effectively orchestrate various technologies, as well as possess both domain and data science skills. Big Data culture has a positive and significant moderating impact on the paths from tangible resources/human skills to Big Data predictive analytics. Big Data predictive analysis has a positive and significant impact on cost and operational performance.
76	Ferraris <i>et al.</i> (2019)	<i>Management Decision</i>	Big data analytics capabilities and knowledge management:	To investigate the impact of BDA and knowledge on firm performance	RBV	There has been little study of knowledge management	BDACs → Firm performance Knowledge Management (KM) orientation → Firm performance BDACs → KM orientation → Firm	Data collected from 88 Italian SMEs	Machine Learning - Big data analytics	Empirical -survey	Firms that developed more BDACs (technological and managerial) than others increased their

			impact on firm performance			generated from the BDA of integrative perspective and combination with firm knowledge.	performance				performance. Knowledge management orientation has an important role in amplifying the impact of BDACs
77	Lee <i>et al.</i> (2019)	<i>Forthcoming at MIS Quarterly</i>	Does IT matter to acquisitions? The impacts of IT distance on post-acquisition performance	To explore the interactions between the acquirer and the target firm in the success of acquisitions, little attention has been paid to the role of IT.	Machine learning theory	In many cases, a lack of attention to IT integration and the resulting IT risks have led to deficiencies in value creation and even acquisition failures.	IT distance → Post-acquisition performance	Using data on U.S. firms' acquisition activities over seven years	IT systems	Empirical – panel data	IT distance is negatively associated with the acquirer's post-acquisition performance.
78	Mikalet <i>et al.</i> (2019)	<i>Journal of Business Research</i>	Big data analytics and firm performance: findings from a mixed-method approach	To test the impact of configurations of resources and contextual factors on performance via BDA investments	Complexity theory	To leverage BDA and improve firm performance, firms must develop strong BDACs	Data Process Technology Organisation People Context → Firm performance	Data from 175 chief information officers and IT managers employed by Greek companies	Machine Learning - Big data analytics	Empirical – survey and case study	Four components of BDA lead to high performance.
79	Mishra <i>et al.</i> (2019)	<i>Management Decision</i>	Organisational capabilities that enable big data and predictive analytics diffusion and organisational performance - A resource-based perspective	To test the impact of IT deployment (strategic IT flexibility, business–BDPA partnership and business–BDPA alignment) and HR capabilities on OP through BDPA	RBV	It is unclear how Big Data predictive analytics (BDPAs) may relate to organisational capabilities and performance.	Strategic IT flexibility → BDPA diffusion Business–BDPA alignment → BDPA diffusion HR capabilities → BDPA diffusion BDPA diffusion → Strategic IT flexibility → OP BDPA diffusion → Business–BDPA partnership → OP. BDPA diffusion → Business–BDPA alignment → OP BDPA diffusion → HR capabilities → OP BDPA diffusion → OP	From 159 Indian companies and received 160 available responses	IT	Empirical – survey	Big Data predictive analytics diffusion mediates the impact of IT deployment and HR capabilities on organisational performance. IT deployment and HR capabilities positively impact Big Data predictive analytics and organisational performance.

80	Oncioiu <i>et al.</i> (2019)	<i>Sustainability</i>	The impact of Big Data analytics on company performance in supply chain management	To understand how BDA improve Romanian supply chain firms and assess their experience, strategies, and professional capabilities to enhance performance	Scenario game theory		Company size → Strategy for implementing BDA Company size → Experience in implementing analytics in the supply chain Years of operating experience → Professional capabilities to develop insights through BDA New tools and technologies → Valuable supply-chain insights Company's experience → Its future intention to implement new tools and technologies to gain valuable supply-chain insights The strategies adopted by companies to implement BDA → Their future intention to implement new tools and technologies to gain valuable supply-chain insights Professional capabilities → Future intention of companies to implement new tools and technologies to gain valuable supply-chain insights Annual sales revenue → The future intention of companies to implement new tools and technologies to gain valuable supply-chain insights Industry → The future intention of companies to implement new tools and technologies to gain valuable supply-chain insights	205 managers	Machine Learning - Big data analytics	Empirical – survey	Firms need to investigate when defining new statistical methods, tools and approaches.
81	Rialti <i>et al.</i> (2019)	<i>Technological Forecasting and Social Change</i>	Big data Analytics capabilities and performance: evidence from a moderated multi-mediation model	To propose and empirically test a model exploring whether organisational ambidexterity and agility mediate the relationship between BDACs	DCV	Notwithstanding the evidence about the impact of BDA, some gaps still exist in this stream of the literature. On the one hand, part of the research is still	BDACs → Organisational performance Mediators: Ambidexterity, agility BDACs → Firm ambidexterity Ambidexterity → Organisational performance BDACs → Agility Agility → Superior performance	259 managers of large European organisations	Machine Learning - Big data analytics	Empirical – survey	Organisational BDACs affect a firm's ambidexterity and agility, which, in turn, affect its performance. Ambidexterity and agility positively mediate the relationship between organisational BDACs and

				and organisational performance		theoretical or, at most, qualitative. On the other hand, quantitative research on BDACs and performance is still in its infancy	Ambidexterity → Agility Organisational BDACs → (a) Ambidexterity (b) agility or (c) performance Moderators: The fit between the organisation and the information management system, organisational resistance to the implementation of an information management system				a firm's performance. Organisational resistance to implementing information management systems and the fit between the organisation and these systems also moderate this relationship.
82	Wang <i>et al.</i> (2019)	<i>British Journal of Management</i>	Leveraging Big Data analytics to improve quality of care in healthcare organisations: a configurational perspective	To test the impact of BDACs on complementary organisational resources and organisational capabilities in multiple configuration solutions leading to higher quality of care in healthcare organisations	Configurational perspective	There is a lack of study on the full complexity of BDA implementations	Configurational elements → Quality of care	3307 senior information system executives remained	Machine Learning - Big data analytics	Empirical – survey	BDA alone cannot achieve the desired outcomes; there is a synergy effect between BDACs, analytical personnel skills and organisational resources and capabilities, which can lead to improved readmission rates and patient satisfaction in healthcare organisations
2018											
83	Anwar <i>et al.</i> (2018)	<i>Journal of Innovation and Knowledge Management</i>	Big Data capabilities and firm's performance: a mediating role of competitive advantage	Examines how Big Data technical capabilities (BDTCs) and Big Data personal capabilities (BDPCs) impact the performance of companies operating in China, one of the world's largest emerging	RBV and DCT	Lack of empirical evidence to understand the impact of BD capabilities on firm performance and competitive advantage (CA)	BDTCs → Firm performance Firm CA BDPCs → FP Firm CA BDTCs → CA → Firm performance BDPC → CA → Firm performance	a sample size of 312 firms	Machine Learning - Big data analytics	Empirical – survey	Big Data's technical and personal capabilities positively impact firm performance and competitive advantage. Competitive advantage partially mediates the relationship between Big Data technical capabilities and firm performance as well as between Big Data personal capabilities and firm performance.

				economies							
84	Caputo <i>et al.</i> (2019)	<i>Management Decision</i>	Innovating through the digital revolution: The role of Soft Skills and Big Data in increasing firm performance	To examine the link among soft skills, information technologies and Big Data for developing a potential insight to link the human and technology components for enhancing firm performance	N/A	What conditions influence HR's adoption of Big Data and AI is unclear.	Human resources emotions → Firms' investment in Big Data Human resources' work motivation → Firm revenues. Human resources' social competencies → Firms' revenues Human resources' organisational behaviours → Firms' investment in Big Data Firms' investment in Big Data → Firms' revenues.	The work personality of 4,758 human resources employed by 72 high-tech European organisations has been assessed	Machine Learning - Big data analytics	Empirical – panel	HR personality, such as work motivation and social competencies, and the firms' economic performance have a strong relationship. Firms' investment in Big Data mediates the relationship between HR organisational behaviour and economic performance.
85	Chae <i>et al.</i> (2018)	<i>Information and Management</i>	Information technology capability and firm performance: role of industry	To investigate how industry impacts the link between IT capability and business performance	Dynamic capabilities	Although researchers call for considering industry in IS value research, few have tested the link between IT and industry benefits.	IT capability (IT leader group and control group) → Firm performance (8 financial ratios) Moderators: industry categories (transform, inform up/down, automate)	Among a set of potential control firms, we chose a control firm whose five-year average sales of the prior five years are within 70–130% of the leader firm.	IT	Empirical – panel	The control group in the industries in which the “transform” IT strategic role dominates demonstrated superior performance over IT leaders The IT leaders in the “automated” IT strategic industry did not exhibit better business performance than the control firms.
86	Chun (2018)	<i>Advanced Science Letters</i>	Machine learning techniques and statistical methods for business applications: implications on Big Data Gold Rush	To examine several Big Data handling techniques, such as machine learning strategies and statistical approaches	Big Data analytics applications (BDAAAs) framework	Some of the challenges associated with big data analysis are the lack of intelligent Big Data sources, the lack of scalable	N/A	/	Machine Learning - Big data analytics	Exploratory - descriptive research methodology	This study pioneered the application of corporate governance as a predictive variable and proposed a hybrid RST, BPN, and DEA approach to predicting corporate performance. Many

						real-time analysis capability, the requirement for network support for applications, the expansion of peer-to-peer networks, the concern for data privacy and information security regulations, issues with data integration and fragmented data, and the need for cost-effective storage systems with higher performance.					businesses rely on data to enhance their performance.
87	Raguseo and Vitari. (2018)	<i>International Journal of Production Research</i>	Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects	To test the impact of BDA investments on the financial performance of a firm, and the mediating role of market performance and customer satisfaction	RBV	Little attention has been paid to BDA solutions and firm performance	The business value of BDA solutions → Financial performance of a firm Mediators: Customer satisfaction, market performance The business value of BDA solutions → Market performance → Financial performance Business value of BDA solutions → Customer satisfaction → Financial performance of a firm	1,962 medium and large French companies to interview from a total of 19,875 registered in the Bureau Van Dijk database.	Machine Learning - Big data analytics	Empirical – survey	BDA enhances the financial performance of a firm. Customer satisfaction has a mediating effect, but market performance does not have a mediating effect.
88	Torres <i>et al.</i> (2018)	<i>Information and Management</i>	Enabling firm performance through business intelligence and analytics: a dynamic	To test the role of business intelligence and analytics (BI&A) in organisations	Sense-seize-transf orm view of dynamic capabilities	There is a need to test the link between BI&A and firm performance via BI&A seizing capabilities and	BI&A technical infrastructure quality → BI&A sensing capability BI&A personal expertise → BI&A sensing capability BI&A management capability → BI&A	A total of 171 responses	Business intelligence	Empirical – survey	Business intelligence and analytics positively impact performance, mediated by business process change capabilities.

			capabilities perspective			business process change in translating BI&A output	technical infrastructure quality BI&A management capability → BI&A sensing capability BI&A sensing capability → BI&A seizing capability BI&A seizing capability → Business process change capability Business process change capability → Functional performance Functional performance → Firm performance				
2017											
89	Cho and Cho (2017)	<i>Advanced Science Letters</i>	A study on the performance and influence of patent development strategy in ICT convergence technology using Big Data	To investigate how SMEs' patent development strategies and ICT convergence technology commercialisation capabilities affect their information performance about patents	Patent development strategy, convergence technology innovation performance and DCs	Following only ICT convergence technology does not easily lead to performance in the realities of the market, and firms do not know how their commercialisation capability affects performance	Patent development strategy → Manufacturing capability Patent development strategy → Production capability Patent transfer strategy → Marketing capability	240 copies except for unfaithful questionnaires	Machine Learning - Big data analytics	Empirical – survey	The ability to commercialise technology and the performance of ICT convergence technology innovation are both positively impacted by the patented technology that research developers in SMEs' development plans possess.
90	Raut <i>et al.</i> (2018)	<i>Benchmarking: An International Journal</i>	The incident effects of supply chain and cloud computing integration on business performance. An integrated SEM-ANN approach	To investigate the impact of cloud computing integration (CCI) and external integration (EI) on the link between the integration of the supply chain and the business performance of the organisation	Contingency theory Organisational information processing theory	A lack of understanding of the concept of SCI	Internal integration → CCI Customer integration → CCI Supplier integration → CCI CCI → External integration (EL) EL → Product cost EL → On-time delivery EL → Product Quality EL → Production flexibility Product cost → Organisational business performance Product quality → Organisational business	296 sample data are collected from the manufacturing sector, 261 (sample data are collected from the service sector, and 103 sample data are collected from the process industry	Cloud computing	Empirical – survey	Production flexibility is a fundamental factor for operational business performance, followed by customer integration, supplier integration, product quality, internal integration and on-time delivery.

							performance Production flexibility → organisational business performance On-time delivery → Organisational business performance				
2016											
91	Chen and Zhang (2016)	<i>Distributed Computing</i>	Evaluating the corporate social responsibility and organisational performance based on large-scale data access and management	To test the impact of corporate social responsibility (CSR) on organisational performance	Organisational citizenship behaviour theory	The application of Big Data has become a critical factor in enhancing the enterprise's competitiveness	CSR (economic responsibility, legal responsibility, ethical responsibility and spontaneous responsibility are components) → Organisational performance	270 questionnaires	Machine Learning - Big data analytics	Empirical – survey	Economic responsibility, legal responsibility, ethical responsibility and spontaneous responsibility are components of CSR. CSR has a positive impact on organisational performance
92	Ramasamy and Ahmad (2016)	<i>Journal of Informatics and Mathematical Sciences</i>	Enhancing decision-making through key information value	To develop a conceptual framework to define and categorise the critical value of information for management strategy	Theory of information value	Many strategies are proposed for organisations using business intelligence applications, but these applications do not inform managers of the value of the information they generate.	N/A	/	Value of information (Vol)	Exploratory - case study	Levels of management are senior, middle and operational management Key information can be organised as values to manage operations and improve the business decision-making processes in the departments
2013											

93	Lin <i>et al.</i> (2013)	<i>Journal of Testing and Evaluation</i>	Corporate performance forecasting using hybrid rough set theory, neural networks, and DEA	To directly forecast corporate performance, this research suggested a hybrid model integrating rough set theory (RST), neural networks (NNs), and data envelopment analysis (DEA)	Rough set theory and neural networks	Despite BPN has outstanding performance, its generalisation ability of its classification or forecasting is influenced by its variable dimensions.	N/A	Taiwan Stock Exchange/Over the Counter (TSE/OTC) listed companies and database.	Machine Learning - Big data analytics	Exploratory	The proposed model performs better than the neural networks model with non-extractable predictive variables and offers a promising alternative for predicting corporate performance.
94	Vukšić <i>et al.</i> (2013)	<i>International Journal of Information Management</i>	Supporting performance management with business process management and business intelligence: A case analysis of integration and orchestration	To understand the utilisation of the potential of BPM and BI in management performance	N/A	There is a lack of studies on the link between business process management (BPM) and business intelligence (BI) to management performance.	Marketing sales and business processes → BIS initiatives Business process management (BPR) → Management performance BIS → Management performance	Both managers responsible for BI and BPM and employees working with these systems on a day-to-day basis.	Business intelligence	Exploratory - interviews	Applying business process management and business intelligence differs significantly from the expected findings. Business intelligence initiatives are usually driven by enhancing marketing sales and business processes. There is a lack of strong commitment to applying both systems to contribute to management performance.
2012											
95	Davis <i>et al.</i> (2012)	<i>Computers and Chemical Engineering</i>	Smart manufacturing, manufacturing intelligence and demand-dynamic performance	To understand the relationships among smart manufacturing, manufacturing intelligence and demand-dynamic performance	N/A	Smart manufacturing is a dramatically intensified and widespread application of networked information-based technologies	N/A	/	Manufacturing intelligence	Exploratory	Smart manufacturing can lead to a dramatic and foundational firm transformation to demand-dynamic economics keyed on customers, partners and the public, firm performance and variability

						throughout the manufacturing and supply chain enterprise.					management. This is related in real-time to computational material engineering, rapid qualification, demand-driven supply chain services, and broad-based workforce involvement. IT-enabled smart factories and supply networks can improve responses to national interests and strategic imperatives. They can revitalise the industrial sector by facilitating global competitiveness and exports, offering sustainable jobs, radically improving performance, and contributing to manufacturing innovation.
96	Saberi and Yusuff (2012)	<i>Neural Computing and Applications</i>	Neural network application in predicting advanced manufacturing technology implementation performance	To understand advanced manufacturing technology (AMT) adoption to predict performance	N/A	AMT adoption is complex, costly and risky, so firms need to understand their current conditions with those of AMT requirements to define the gaps and predict their performance	N/A	Data were collected from a survey of 140 SMEs	Manufacturing technology	Empirical – survey	A framework is developed to understand advanced manufacturing technology implementation outcomes and predict firm performance.
97	Uwizeyemungu and Raymond (2012)	<i>Technology Management</i>	Impact of an ERP system's capabilities upon the realisation of	To understand the potential relationship between the	RBV	It is beneficial to identify the antecedents of IT business value	ERP capability (ERP capability, ERP integration, ERP flexibility) → Organisational performance	25 in-depth interviews with different managers, including the firm's CIO	IT	Exploratory – case studies	All ERP capabilities have a significant impact on organisational performance.

			its business value: a resource-based perspective	essential characteristics of an ERP system that can consequently influence organisational performance							There are different ERP impacts on organisational processes and their relative importance in improving business value.
2011											
98	Kim <i>et al.</i> (2011)	<i>Journal of the Association for Information Systems</i>	IT capabilities, process-oriented dynamic capabilities, and firm financial performance.	To examine and empirically test the influencing relationships among IT capabilities (IT personnel expertise, IT infrastructure flexibility and IT management capabilities), process-oriented dynamic capabilities and financial performance	DCs	N/A	IT capability (IT personnel expertise, IT infrastructure flexibility, IT management capability → Financial performance Mediators: process-oriented dynamic capabilities (PDCs) of a firm	The firms in the DART System, supervised by the Financial Supervisory Service of the Korean Government, were adopted as a sampling frame. This system includes a mailing list of 1,835 firms, comprising 629 firms listed on the Korea Stock Exchange and 857 firms listed on the Korea Securities.	IT	Empirical – survey	Process-oriented dynamic capabilities can connect business parties, reduce process costs, and capitalise on business intelligence and analytics, mediating between IT capabilities and financial performance.
2008											
99	Ruhle <i>et al.</i> (2008)	<i>Libyan Journal of Medicine</i>	Impact of robotic dispensing machines in German pharmacies on business performance indicators	To investigate the influence of robotic dispensing machines in community pharmacies on staff efficiency and sales of over-the-counter	N/A	No adequate scientific examination has been conducted of manufacturers' claims	N/A	253 customers who were using a ROWA robotic dispensing machine of type ROWA Select in 2007 from German pharmac	Robotic	Empirical –survey	Most of the pharmacies (79%) retrofitted robotic dispensing machines. A total of 59% of pharmacies gained space for self-service and behind-the-counter displays

				drugs							
1995											
100	Mukhopadhyay <i>et al.</i> (1995)	<i>MIS Quarterly</i>	Business value of information technology: a study of electronic data interchange	To test the impact of electric data interchange on IT business values	N/A	IT business values have mixed results: some have found positive impacts, but some have seen negative or no consequences.	Transaction sets and the application systems interfacing with EDI to determine the locus of impact The extent of the EDI network (e.g., the number of trading partners) to assess the magnitude of the impact The production/operation process to identify control variables Determine the exogenous industry or economy-wide trends that may mitigate the results	This data covers nine assembly plants over the period 1981 through 1990 model years.	Business value of information technology	Empirical – panel data	The savings per vehicle that result from improved information exchanges are estimated to be about \$60. Including the additional savings from electronic document preparation and transmission, the total benefits of using electronic data interchange per vehicle amount to over \$100. System-wide, this translates to annual savings of \$220 million for the company
1990											
101	Floyd and Wooldridge (1990)	<i>Journal of Management Information Systems</i>	Path analysis of the relationship between competitive strategy, information technology, and financial performance	To test the influence of competitive strategy on IT and of IT on organisational performance	Competitive strategy	It is essential to understand the misalignment of IT and strategy	Human resource differentiation → Organisational performance Product differentiation → Organisational performance Technology leadership → Organisational performance Market share orientation → Organisational performance Cost orientation → Organisational performance Segmentation → Organisational performance Product breadth → Organisational performance	127 banks and interviews with 68 bank CEOs	IT	Empirical – survey	The strategy appears to have direct effects on IT, and IT has a direct impact on ROA. IT plays a vital role in the strategy-ROA relationship.