Nontechnical and Technical Artificial Intelligence Capability: Their Antecedents and Impacts on Firm Performance

A thesis submitted for the degree of Doctor of Philosophy

by

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Abstract

Artificial intelligence (AI) has attracted huge attention in management field. Its application in organizations has become a common phenomenon. Academics are actively studying how to promote firms to use AI techniques more effectively and the impact of this phenomenon. Especially based on the resource-based view (RBV), scholars have investigated the resources and capabilities that are helpful for firms to apply AI, and developed relevant concepts such as AI capability (AIC). However, there are still many issues that have not been studied, for example what factors can facilitate the improvement of AIC, what factors affect the relationship between AIC and organizational performance, etc. In order to fill these research gaps, this study proposes organizational and contextual antecedents that may influence the development of firm AIC based on RBV and institutional theory. Through the review of AI research, the concepts of nontechnical AIC (NAIC) and technical AIC (TAIC) are constructed from the perceived divergence of nontechnical and technical research. It also proposes corresponding conceptual model and empirically tests the relationships between NAIC and TAIC and different antecedents, as well as how they ultimately affect firm performance. The data was collected from 206 firms in the Yangtze River Delta region of China that have used AI techniques for more than a year. SPSS is used to perform structural equation model analysis and test hypotheses. Data analysis results show that exploitation strategy, coercive pressure, and mimetic pressure can improve firm NAIC. Exploration, leaders' AI knowledge, and mimetic pressure will improve firm TAIC, and these relationships are moderated to varying degrees by the firm's data-driven culture. NAIC and TAIC both have a very significant positive impact on firm performance, and they are also moderated by firm international presence. These findings confirm the feasibility of understanding and studying AIC from the perspective of technical relevance, make theoretical contributions to AI-related research, and provide suggestions for management practices of firms applying AI techniques.

Keywords: artificial intelligence, artificial intelligence capability, resource-based view, institutional pressure, firm performance

Declaration

I hereby declare that this thesis is based on my original work. It was conducted in accordance with the University Code of Research Ethics. This thesis has never been submitted for a degree in this or any other university.

Acknowledgment

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List of Abbreviations

AGI Artificial General Intelligence

AI Artificial Intelligence

AIC Artificial Intelligence Capability

ANN Artificial Neural Networks

API Application Programming Interface

AVE Average Variance Extraction

B&M Business and Management

BDAC Big Data Analytics Capabilities

CDO Chief Digital Officer

CEO Chief Executive Officer

CFA Confirmatory Financial Analysis

CFO Chief Financial Officer

CIO Chief Information Officer

COO Chief Operating Officer

CR Combined Reliability

CTO Chief Technology Officer

CP Coercive Pressures

DDC Data-Driven Culture

DL Deep Learning

DOI Diffusion Of Innovation

EFA Exploratory Factor Analysis

EJRC European Joint Research Centre

EXPR Exploration

EXPT Exploitation

FP Firm Performance

GPU Graphics Processing Units

INT International presence

IT Information Technology

ICT Information and Communications Technology

IS Information System

LAIK Leaders' AI Knowledge

ML Machine Learning

MP Mimetic Pressures

NAIC Nontechnical Artificial Intelligence Capability

NP Normative Pressures

R&D Research and Design

RBV Resource-Based View

REC Research Ethics Committee

SEM Structural Equation Modelling

SLR systematic literature review

STARA Smart Technologies, Artificial intelligence, Robotics, and Algorithms

TAIC Technical Artificial Intelligence Capability

TAM Technology Acceptance Model

TOE Technology-Organization-Environment

TPB Theory of Planned Behaviour

TRA Theory of Reasoned Action

UTAUT Unified Theory of Acceptance and Use of Technology

VRIN Valuable, Rare, Inimitable, Non-substitutable

YRD Yangtze River Delta

Chapter 1: Introduction

1.1 Background

As the competitive landscapes are subject to rapid changes, organizations in the digital age demand faster responses and greater attention to the changing scenarios (Venkatraman, 2017). In light of this, many firms are using new technologies in an attempt to obtain high performance and competitive edge (Weill and Woerner, 2017). Among these technologies, artificial intelligence (AI) has taken centre stage and attracted interest from both commercial and academic publications. According to Davenport (2018), AI might be the greatest disruptive force in contemporary technology. Similarly, Brynjolfsson and McAfee (2017) assert that AI stands for the most significant general-purpose technology nowadays, especially in terms of machine learning techniques.

AI is for the purpose to comprehend and create a machine that can do intelligent activities. It may be essential to the second machine age and aid in people’s ability to control the material and mental environments, which will ultimately lead to prosperity for everyone (Brynjolfsson and McAfee, 2014). For many years, researchers have experimented with building a "thinking machine". But given the recent advancements in AI, it should be given careful thought on how these technologies will affect the world in the future (Kurzweil et al., 1990; Kurzweil, 2005; Agrawal et al., 2017). The world is changing very quickly so that firms are facing a ton of opportunities. Organizations could employ AI to optimize their operation, marketing, and human resource departments (Baryannis et al., 2019; Sterne, 2017; Sivathanu and Pillai, 2018; Stone et al., 2018). Adoption of AI also offers benefits from its unrealized potential and demands a further thorough analysis (Chui and Malhotra, 2018).

Despite AI not being a novel term, it has attracted significant interest in recent times (Ransbotham et al., 2018). According to Davenport and Ronanki (2018), it is anticipated that this phenomenon would cause many transformations to companies globally, involving various sectors. Firms that use AI techniques could expect to gain enhancements in terms of increased business value, such as greater profitability, reduced costs, and improved operational efficiency (AlSheibani et al., 2020). Based on a survey conducted by MIT Sloan Management Review, over 85% of surveyed companies see AI as a way to get a competitive edge, while over 80% consider it a strategic opportunity (Ransbotham et al., 2017). Consequently, many companies are allocating resources towards implementing AI strategies with the aim of attaining competitiveness. In spite of the growing interest in AI, many organizations still struggle to fully take its advantages (Fountaine et al., 2019). With the considerable investment of time, effort, and resources by companies in the adoption process, the expected advantages of AI did not materialize (Makarius et al., 2020). The integration of AI into organizational operations brings up a new array of challenges and complexities (Duan et al., 2019). Examples of relevant tasks include identifying, integrating, and cleansing diverse data sources (Mikalef and Gupta, 2021), connecting knowledge from different domains to develop accurate and meaningful models (Duan et al., 2019), and incorporating AI applications into existing processes and systems (Davenport and Ronanki, 2018). In order to effectively harness the potential advantages of AI, organizations need to understand both the capacity of these technologies to create value and the strategies to overcome the associated challenges. Dwivedi et al. (2021) have identified areas in research that need more investigation, while Mikalef and Gupta (2021) have examined the specific resources required by companies to develop AI capability and implement AI techniques. However, it still has not been fully understood how internal and external factors stimulate the growth of organizational AI capability and the mechanisms by which value is generated in terms of organizational performance. Besides, Kinkel et al. (2022) have also called for future research on: 1) incorporating employee soft skills and the dynamic capabilities of the firm as an organization into considerations for AI technique usage; 2) investigating how AI technique usage affects employee skills, firm performance, and firm competition and internationalization strategy; 3) adding moderating and/or mediating variables to the relevant models for further analysis (e.g., Rialti et al., 2019).

1.2 Statement of the problem

Firms now have additional options because of rapid progress made in AI (Hughes et al., 2022; Obschonka and Audretsch, 2020; Shareef et al., 2021). AI may result in increased productivity, lower costs, more quality products, and better customer support (Bag et al., 2021). Companies may use AI to enhance consumer experiences by offering more affordable solutions and more suitable suggestions (Payne et al., 2021). To find business prospects, a firm's capability is essential (Yao et al., 2021). Although organizations confront formidable obstacles when using AI (Yu et al., 2021), AI capability (AIC) has the potential to significantly boost business performance (Mikalef and Gupta, 2021). The resource-based view states that organizational AI usage essentially means utilising a group of resources (Bag et al., 2021; Mikalef and Gupta, 2021). These resources consist of data, techniques, labour skills, organizational coordination, and other support (Kim, 2019; Selz, 2020). A firm gains a competitive edge and enhances its performance when it has access to resources that are difficult for another organization to duplicate (Yasmin et al., 2020; Chen and Lin, 2021). Meanwhile, through the use of AI, digital methods are being introduced into the work culture (Furman and Seamans, 2019), which in turn generates a data-driven organizational culture (Chatterjee et al., 2021). This change is more pronounced in business units (whether public or private) (Wirtz and Muller, 2019). However, at the internal level, there has not been sufficient research on how firms can accumulate resources to directly enhance AIC through strategic choices and leveraging leaders' abilities (research gap 1).

On the other hand, DiMaggio and Powell (1983) point out that external factors increase the uncertainty and constraints of organizations, so the rationality of organizational participants in coping with pressure leads to the homogenization of organizational domains, a phenomenon known as institutional isomorphism. Isomorphism occurs through three aspects of institutional pressures: 1) coercion, through political influence and legitimacy issues; 2) imitativeness, where uncertainty leads to standardization; 3) normative, which is related to the norms associated with specialization (DiMaggio and Powell, 1983). As a popular theory for explaining organizational behaviour, institutional theory emphasizes that organizations seek social legitimacy for themselves (DiMaggio and Powell, 1983). Institutional pressures from outside the organization have an impact on its behaviours, tactics, and choices (Kuo et al., 2022). Their competitive advantage is increased by this legitimacy, which also gives them access to valuable and rare resources (Chu et al., 2018; Jiao et al., 2022; Yang and Su., 2014). Information systems (IS) research has been done to identify the requirements and barriers that impact a firm's adoption of new technology from this perspective (Chatterjee et al., 2021; Krell et al., 2016), such as how institutional pressures affect firms adopting big data analytics to improve costs and operational performance (Dubey et al., 2020; Jiwat and Zhang, 2022). However, distinct from the adoption phase, the role of external factors (institutional pressures) during an organization's use of AI techniques needs to be better understood. In addition, due to the different institutional environments in different countries, the mechanism by which the AI capability of Chinese firms is affected by institutional pressure also needs to be further studied (research gap 2).

Faraj and Leonardi (2022, p.780) state that "the time has come for strategy scholars to make the role of technology a core theoretical and empirical concern". As the relationship between business and technology has undergone tremendous change, organizations are no longer simply owning the technology or entering into contractual agreements with other companies that can provide it (Faraj and Leonardi, 2022). Today's AI application is a series of relationships distributed among many companies (Gligor et al., 2021). Effectively navigating these relationships is complex but crucial for maintaining the competitive advantage (Faraj and Leonardi, 2022). Hence, it is very valuable from both a theoretical and practical standpoint to investigate the process and key components that contribute to the influence of AIC on firm performance (Chen and Lin, 2021; Mikalef et al., 2021). Research has noticed that the use of AI techniques and firm success may be influenced by dynamic changes in the business environment (Bag et al., 2020; Dubey et al., 2020). However, existing studies lack relevant moderating variables to further prove the relationship between AIC and firm performance (research gap 3).

1.3 Research aims and objectives

This research aims to contribute to the understanding of the relationships between firm's exploration / exploitation strategies, leaders' AI knowledge, institutional pressures, AI capability, and performance. The following objectives will enable the aim to be achieved:

1. To study the concepts and dimensions of AI, especially AI capability, and identify its antecedents through literature review.

2. To develop a conceptual model and formulate the necessary hypotheses to illustrate the roles of AIC and other related variables.

3. To conceptually and empirically investigate the relationships between AIC and its different antecedents, as well as its impact on firm performance, in order to answer the research questions.

4. To generate implications for the related theories and practice based on results and findings, and provide suggestions for future research.

1.4 Research questions

There has been much research done on how AI affects business performance (Denicolai et al., 2021; Mikalef and Gupta, 2021), including sectors of financial services (Huynh et al., 2020), manufacturing (Bag et al., 2021), logistics (Chien et al., 2020), automated retailing (Pillai et al., 2020), marketing (Keegan et al., 2022), coaching services (Kim et al., 2021), and customer relationship management (Chatterjee et al., 2021). The focus of these studies was on the influence of AI on business innovation processes and management practices (Liu et al., 2020), as well as the connection between AI learning and entrepreneurial success (Khalid, 2020). On the other hand, there is still a lack of understanding on how AIC affects a firm's performance and how it could be better explained. The explanation of AIC is mainly from a nontechnical perspective, while the technical aspects of AI, which may potentially have a major impact on firm performance, are not given the same weight. In order to fulfil the study goals, the following research questions are thus developed:

1. To what degree do different organizational (exploration, exploitation, leaders' AI knowledge) and contextual (institutional pressures) factors influence firms' nontechnical and technical AIC development?

2. To what degree does firms' nontechnical and technical AIC development influence firm performance, and is this relationship moderated by any factors?

3. What is the difference between how nontechnical and technical AIC are affected by the antecedents and how they impact firm performance?

1.5 Main contribution of this study

This study draws on existing theories and research achievements to establish relevant conceptual model and hypotheses. This model considers multiple factors at the organizational and contextual levels to explore and explain the different antecedents that promote the growth of firm AIC, as well as the further impact of AIC on firm performance, with the corresponding mechanisms interpreted. This study refers to two classic theories in management: resource-based view (RBV) and institutional theory (Oliver, 1997), to construct related concepts and model. Reference is also made to the existing AIC conceptual framework (Mikalef and Gupta, 2021). It is therefore consistent with existing research on a theoretical basis. By integrating existing theories and research, this study proposes a relationship model in which exploration/exploration strategies, leaders' AI knowledge, and institutional pressures serve as antecedents of AIC that improves firm performance. This study examines and explains this model and how some of the relationships are moderated by variables such as data-driven culture and firm international presence, thus making contributions to theory and practice.

Specifically, the contributions of this study are threefold. First, it contributes to knowledge of AI research in the management field. Through a literature review, this study demonstrates that due to the complexity of AI, there are technical and nontechnical divergences in management AI research. Such divergences appear in many aspects such as research topics, conceptual understanding of AI, research theories and methods, etc. Therefore, when conducting research in this area, one needs to take these divergences into account or strive for knowledge integration across disciplines. Based on this argument, this study innovates the concept of AIC. According to the correlation between different resources and the development of AI techniques, AIC is divided into nontechnical and technical to distinguish its different connotations. On this basis, the conceptual model with NAIC and TAIC as the core is tested to demonstrate the related antecedents and consequences of the two. It also helps theoretically and practically understand the effective mechanism of how to use AI techniques to achieve business value.

Second, it contributes to RBV and institutional theory. Previous research has used RBV to understand the resources required by organizations to adopt and apply AI techniques (Ashaari et al., 2021; Bag et al., 2021). AIC also explains the ability of firms to select, orchestrate, and leverage AI-related resources (Mikalef and Gupta, 2021). However, the antecedents of this ability have not been well studied. For example, previous research has confirmed the impact of AIC on marketing capabilities (Mikalef et al., 2023), organizational creativity (Mikalef and Gupta, 2021), and data-driven culture (Wamba et al., 2024a). However, no research has understood the growth dynamics of AIC and whether these influencing relationships are moderated by any other factors. The factors within the organization affecting AIC considered in this study include exploration/exploration strategies and leaders' AI knowledge, while the external factors are institutional pressures. The introduction of institutional pressures comes from institutional theory. Previous research on institutional theory has examined the impact of different institutional pressures on the adoption of AI or other new technologies (Bag et al., 2021; Behl et al., 2022; Dubey et al., 2019a; Hsu et al., 2012). Based on the reality of large-scale AI applications in Chinese firms, this empirical study demonstrates the impact of institutional pressures on the AI usage stage, making further contributions to institutional theory. In addition, this study refers to previous related research and introduces data-driven culture (Dubey et al., 2019a) and firm international presence (Bhandari et al., 2023) as moderators to make further contributions to RBV-based AIC research.

Finally, this study provides implications for managers in practice and policy makers. Managers need to make exploration and/or exploration strategic decisions based on different situations and the nontechnical or technical AI-specific resources needed by the firm. Managers should also improve their own level of AI knowledge to strengthen firm technical AIC, while paying attention to the moderating influence of DDC. Coercive pressure has a positive impact on nontechnical AIC of Chinese firms. Therefore, managers should draw more motivation from legal and policy aspects. Policy makers should also attach importance to the rationality of legal and policy formulation and provide positive guidance to firms. Mimetic pressure can also stimulate the improvement of different AICs in firms. In terms of AIC's impact, managers need to seriously consider the more important role of nontechnical AIC on firm performance, as well as the moderating role of firm international presence.

1.6 Thesis structure

This thesis consists of seven chapters. Chapter 1 begins with introducing the background of this study. Then it provides a rationale of the research, explains the research context and gaps, and states the research problems. It further highlights the research objectives and raises the research questions, followed by a brief introduction to the contribution of this study. Additionally, the structure of this thesis is described as an overview.

Chapter 2 is the literature review. It first introduces the concept of AI, which is a key conceptual foundation of this research. Based on the existing literature, it explains the basic definition of AI, the characteristics of AI, and the application of AI in business and management. Secondly, it reviews the relevant research on AI in the field of business and management, identifying the main divergences from two different aspects of nontechnical and technical research. Then it introduces the basic concept and existing research of AIC, and explores and expounds the different antecedents of AIC at the organizational and contextual levels.

Chapter 3 explains the theoretical foundation of this paper. Based on the theories, reasonable hypotheses are proposed and explained according to the findings from literature review. With these hypotheses, the conceptual model of this study is further developed to reflect the research questions and incorporate all relevant variables.

Chapter 4 describes the method and process of this study in detail. It first provides an overview of different research philosophies, approaches, methodologies and makes reasonable choices. Then, the background and design of this study are discussed. Regarding questionnaire design, this chapter explains the meaning and measurement of each variable and how they are reflected by the questionnaire items. In addition, it describes the process of data collection and demonstrates the validity and reliability of the collected data.

Chapter 5 describes the process of data analysis and the empirical results obtained. First, the collected questionnaire responses are screened and descriptive analysis is done on the filtered data. Then, confirmatory factor analysis and other methods are used to optimize the measurement items and evaluate the validity and reliability. Finally, the structural equation model is used to test the conceptual model and related hypotheses.

Chapter 6 discusses the findings of the empirical test results, and on this basis expounds the theoretical and practical contributions of the study. The implications of the study for AI-related policy making are further discussed.

Chapter 7, as the last chapter of this thesis, answers the research questions proposed by this study as the conclusion for the full thesis. It also reflects on the limitations of this study and puts forward suggestions for potential future research directions.

Chapter 2: Literature Review

2.1 Introduction

The term Artificial Intelligence was first proposed by McCarthy in 1955, who defined it as the science and engineering of making intelligent machines (McCarthy et al., 2006). Since then, the area of AI has progressed in two distinct directions: the human-centric approach and the rationalist approach (Borges et al., 2021). The human-centred approaches include the formulation of hypotheses and the subsequent validation via experimentation, constituting an integral component of empirical research (Haugeland, 1989; Kurzweil et al., 1990). The rationalist ones consist of a fusion of engineering and mathematics, as discussed by Charniak (1985), Luger (1998), and Winston (1970). AI draws inspiration from several disciplines but is initially focused on developing software and hardware capable of performing cognitive tasks (Bundy et al., 1978; Russell and Norvig, 2016). According to the rationalist approach, the area of AI includes any technique that allows robots to imitate human conduct in order to reach the optimal outcome, or the predicted best outcome in some circumstances (Russell and Norvig, 2016).

From an organizational perspective, studies during the early stages of AI started to focus on decision-making in the middle of the 1960s (Buchanan and O'Connell, 2006). During that time, the area of AI addressed issues that could be summed up in a set of mathematical formulae (McCarthy and Hayes, 1981). Since the 1980s, AI has been utilised in business. Numerous firms have invested in and worked to develop computer vision systems, robotics, and expert systems, in form of software and hardware (Boden, 1984; Russell and Norvig, 2016). Furthermore, according to Holloway (1983) and Porter and Millar (2009), back then AI was already being mentioned as a strategic instrument to enhance organizational difference in a competitive environment.

Three main elements have contributed to the growth of AI knowledge in various disciplines and its increasing popularity: large amount of data, advanced algorithms, and more powerful computing hardware (Brynjolfsson and McAfee, 2017). Due to these progress, technology-focused organizations are becoming more interested in AI techniques. Consequently, Google, Amazon, IBM, and many business giants began to provide cloud-based machine learning infrastructure, making cognitive techniques easier to acquire and use (Brynjolfsson and McAfee, 2017; Davenport, 2018; Venkatraman, 2017). AI can be viewed as a technology that has been introduced as a way to simulate human performance with the capacity to draw its own conclusions through self-learning, which can support or even replace human cognition in tasks requiring human thought (Jarrahi, 2018). In general, speed, flexibility, customisation, size, creativity, and decision-making needed by organizations may all be improved with the use of AI techniques (Venkatraman, 2017; Wilson and Daugherty, 2018). Furthermore, firms stand to gain from using AI to create value in a variety of business domains, including process automation, obtaining knowledge from data for decision-making, interacting with clients and staff, and developing and delivering new goods and services (Davenport and Harris, 2017; Davenport and Ronanki, 2018; Davenport, 2018; Mikalef et al., 2019b; Ransbotham et al., 2018; Westerman et al., 2014b).

In order to answer the research questions raised in Chapter 1, it is necessary to review the literature to summarize the research progress in related fields and identify research gaps. This chapter will mainly focus on the core concepts of this study - AI and AIC, by reviewing their concepts and related research. Specifically, it will first describe the basic concepts and characteristics of AI and distinguish it from other digital technologies. Then, the research on different aspects of AI adoption, application and impact in business and management is elaborated and reviewed. Next, the concept and dimensions of AIC are described in detail, and its facilitating factors studied in this thesis are explained. Through the above content, the preliminary construction of this research is carried out.

2.2 Artificial intelligence

2.2.1 The concept of AI

It is difficult to provide a broadly agreed definition of AI because of its multidisciplinary character, which encompasses disciplines of information science, anthropology, engineering, business, medicine, linguistics, etc. The European Joint Research Centre (EJRC) proposes an operational definition, based on knowledge and research from a High-Level Expert Group, which refers AI systems to "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal" (Samoili et al., 2020, p.9). Depending on the discipline, scholars categorize AI in terms of its ability to imitate human behaviour and thoughts or to behave or think rationally. Computer scientists see AI as machines, computers or computer systems that imitate cognitive functions that are normally associated with the human mind, such as learning and problem solving (Russell and Norvig, 2016), while scholars in business and management field prefer to interpret AI as "a system's capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019, p.5). This definition proposed by Kaplan and Haenlein (2019) is also the conceptual foundation for the term AI in this research.

AI is a buzzword that covers a range of concepts and techniques, including machine intelligence, computational intelligence, hybrid augmented intelligence, deep learning, and neural network (Donepudi, 2017). It first emerged in the 1950s as a subject within computer science. In 1956, John McCarthy first introduced AI as the field of studying and creating intelligent machines, especially advanced computer programs. Currently, the emphasis of AI has significantly shifted compared to the last century. The interest in AI has expanded to quite a few domains, such as education (Hunter, 2018), healthcare (Yu and Kohane, 2018), public administration (Agrawal, 2018), and business and management (Brynjolfsson and McAfee, 2017). According to its definitions in literature, AI encompasses a range of tools and technology that may improve and increase organizational performance (Mikalef and Gupta, 2021). This is accomplished by developing intelligent systems that can address complicated environmental issues, and such intelligence is defined as the emulation of human-level intellect (De Bruyn et al., 2020; Figueroa-Armijos et al., 2023). This notion acknowledges that AI is a sophisticated system that requires consideration of both technical and nontechnical aspects (Samoili et al., 2020, p.5). There has also been ongoing discussion over the potential dangers of AI, particularly in relation to job displacement (Rotman, 2013), malfunctions in autonomous devices (Buchanan, 2005), and the erosion of privacy (Manheim and Kaplan, 2018).

Some researchers also think it would be better to restrict the meaning of the term artificial intelligence to artificial general intelligence (AGI), which is the intelligence of a machine capable of understanding or learning any intellectual task that a human being can (Goertzel, 2014; Thórisson et al., 2015). So far, machines can only be trained to do certain and well-defined tasks, for example, playing chess, identifying faces, and forecasting market prices.

Because these algorithms are limited to the specific area in which they have been trained to work. These are frequently referred to as "weak AI" or "narrow AI" (Wang and Siau, 2019). But any cognitive activity can theoretically be acquired, since learning itself is a cognitive action. As a result, "strong AI" or AGI may one day be able to be programmed to learn and adapt on their own (Kurzweil, 2005). However, the majority of scientists still believe that humans are decades away from the realization of AGI, therefore "weak AI" will continue to be the focus of this study. The four primary competencies that any AI should have are perception, comprehension, action, and learning (Bowen and Morosan, 2018). AI techniques including deep learning, machine learning, computer vision, image recognition, and natural language processing, make these capabilities possible (Bawack et al., 2019; Duan et al., 2019).

There are also some scholars who classify AI in other ways based on research fields and applied situations. For example, Huang and Rust (2018) start from the needs of service functions and classify AI into mechanical, analytical, intuitive and empathetic in order from low to high levels. Later, they further refine the concept on this basis and divided AI into three levels: mechanical, thinking, and feeling (Huang and Rust, 2021). Combining the role of AI in the healthcare industry, Garbuio and Lin (2019) group AI into three categories: assisted intelligence, augmented intelligence, and autonomous intelligence. These classification methods have contributed to research on the concept of AI as well and have been widely cited in the literature.

2.2.2 Differentiating AI and other digital technologies

Some researchers view AI as one of digital technologies or a part of digitalization (Kraus et al., 2018; Silvia, 2020; Watson et al., 2018). This might not be wrong, but it would ignore some unique advantages of AI and make the concept and characteristics of AI ambiguous and confusing. According to Gartner (2018), “digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities; it is the process of moving to a digital business”. On the other hand, AI represents “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan and Haenlein, 2019, p.5). While digital technologies are considered to make business operate more efficiently and automatically, AI emphasizes the self-learning ability of its technological nature and thus differentiates itself from normal information and communication technologies (ICT).

According to Legner et al. (2017), the process of business digitalization can be divided into three stages. With regard to regular automation, the first level highlights the benefits of ICT. To help with planning, control, coordination, and decision-making in organizations, Adetayo et al. (1999) draw attention to the procedures that gather, retrieve, process, store, and distribute information. The advantages of the World Wide Web are highlighted in the second part. Autio (2017) demonstrates it eventually gives a chance for business model innovations that include drastically altering and reconsidering value creation via interactions with stakeholders both internally and externally, same for value capture and value delivery. Today, the challenge is to take on the third step, which includes the Internet of Things, big data, robotic systems, additive manufacturing, and the massive power that comes with computers' ability to store and analyse information. To get a better understanding of both internal and external activities and to make the best management and strategic choices possible, firms must integrate big data and business analytics throughout their whole organization (Charalabidis et al., 2015).

Automation brought forth by different digital technologies promises increased production along with enhanced efficiency, safety, and convenience (Javaid et al., 2021). Additionally, the nature of labour is altered by these digital technologies, giving rise to whole new categories of virtual or digital labour (Valenduc and Vendramin, 2017). According to Jepsen and Drahokoupil (2017), digital technologies will alter the need for workers, skill requirements, income volatility, and tax bases. Employees and firms seeking to expand in the digital age must acquire new skills (Ciarli et al., 2021). The logic of value production is likewise altered by digital technologies (Gregori and Holzmann, 2020). Based on Autio et al. (2016), these technologies improve (by becoming more accessible and efficient), expand (beyond the fundamental exchange of goods and services), and enrich (by making organizations more intensely data-driven) such logic, hence increasing firms’ capacity to co-create value. Thus, digital affordances are a powerful force behind the development of new business models. The traits of the top management team (TMT), and in particular the senior management's digital awareness and abilities, are also crucial for fostering success in global marketplaces and ensuring the long-term viability of the company (Velinov et al., 2020). Furthermore, firms that have a Chief Information Officer or Chief Digital Officer on board are often more global than those that do not have these two roles in senior management (Velinov et al., 2020). The advantages of digital technologies affected client acquisition, customer service, competitiveness development, as well as image and brand improvement (Kannan, 2017). According to Fernández-Portillo et al. (2024), a considerable percentage of organizations saw that digitalization had an impact on improved business processes, tighter stakeholder interactions, and new business prospects.

Powerful resources for information storage and processing are now readily accessible due to recent technical advancements. An atmosphere that is conducive to business is created by the broad use of digital technology. It presents chances to enhance value production. Companies must change every aspect of their operations and organization itself in order to identify opportunities and use the tools at their disposal (Kraus et al., 2019; Matt et al., 2015). Furthermore, disruptive shifts in the value chain are brought about by digital technologies since they assist firms at several levels, including creation, production, marketing, delivery, and support (Porter and Heppelmann, 2015). Two stages of digitalization were identified by Ross et al. (2017): becoming digital and being digitalized. Implementing technology and software to optimise operations and standardise business processes constitute the first phase, which happens at the operational level. In order to establish a new value proposition, the second stage uses digital technology to target, communicate, and personalise alternative offerings. Therefore, a firm becomes digital by seizing the chance to reconstruct its operations and business model (Aagaard, 2019; Kraus et al., 2019; Ross et al., 2017).

AI is often related to devices that are capable of learning, thinking, making decisions, and exhibiting creativity (Rai et al., 2019). Machine learning, natural language processing, computer vision, knowledge-based reasoning, and robotics are a few techniques that AI systems are founded on (Benbya et al., 2021; Stone et al., 2016). Machine learning (ML) or deep learning (DL) are at the heart of many applications dubbed AI (Berente et al., 2021; Janiesch et al., 2021). IS research has started to formulate the distinctive features of current ML-based AI systems (e.g., Ågerfalk, 2020; Benbya et al., 2021). Three interconnected qualities of AI systems are proposed: autonomy, learning, and inscrutability (Berente et al., 2021). The capacity of AI to function independently of human input is referred to as autonomy. The term "learning" describes AI's capacity to advance via information and experience (Ågerfalk, 2020; Janiesch et al., 2021). According to Astitani et al. (2021) and Jöhnk et al. (2021), inscrutability is the inability of AI to be understood by certain audiences because of its intricate internal workings and probabilistic outputs. These traits should become more pronounced when new AI techniques are developed (Berente et al., 2021). These distinctive qualities and their socio-technical ramifications must be addressed by organizations looking to get benefit from AI (Böttcher et al., 2022; Berente et al., 2021).

Table 2.1: Main differences between AI and normal digital technologies

	AI	Normal digital technologies
Context	Boost of intelligent systems and applications	Extensive utilization of Internet, big data, cloud computing and other technologies in various industries
Application scope	Integration and optimization of whole system	Linkage of multiple systems with tendency toward overall optimization
Main focus	Driving flexible innovation and smart business operation	Improving the level of automation and decision-making efficiency
Essence	Human-AI/machine interaction ("human in the loop")	Human-machine integration (lack of connection)
Main goal	To make the object have functions of sensitive and accurate perception, correct thinking and judgment, adaptive learning, as well as effective execution	To make business and technology really interact and change the traditional business models, based on the support and ability provided by information and digital techniques

There has not been much discussion around how to differentiate AI from previous digital technologies. Based on their definitions, AI could be understood as the developing trend or ultimate goal of digital technologies (Lu et al., 2019). Information digitization has been a defining feature of digital transformation so far, serving as a kind of preparatory stage for moving an organization's operations and programmes online (Mergel et al., 2019). Digital transformation, which began with external (customer-facing) programs and was fuelled by marketing, expanded into internal and cross-functional initiatives throughout the social media era (Gong and Ribiere, 2021). Conversely, huge data is the main source of power for AI (O'Leary, 2013). It originated with analytics, which has connections to almost every discipline (Xu et al., 2021). As a result, while digital technologies have led to the spread of different systems, AI gains from system integration. Digital technologies facilitate the evolutionary stage of a firm's digital transformation, which comprehensively optimizes business operation with the support of big data and cloud computing technologies. AI, however, means the more advanced stage of a firm's transformation, which is the intelligent application of data as a factor of production with the support of AI techniques. Table 2.1 summarizes their main differences in various aspects.

As more scientific breakthroughs were made, the main techniques of AI now include neural network, fuzzy system, heuristic algorithm, etc., which represent the novel directions and trends of development for digital technologies (Bughin et al., 2017). In other words, these are also the advancements that have not been or cannot be realised based on traditional digital technologies. To conclude, compared with normal digital technologies, AI is featured with functions of anthropomorphic intelligence, such as self-adaptation, self-learning, self-correction, self-coordination, self-organization, self-diagnosis, or self-repair (Issa et al., 2022).

2.2.3 Use of AI in business and management

2.2.3.1 Organizational adoption of AI

The majority of the obstacles to AI adoption that have been noted in the literature generally have to do with certain features of the technology itself. For instance, firms have challenges with data such as poor data quality, incompatibilities, exorbitant expenses, and a dearth of tailored solutions (Lee et al., 2018b; Dukino et al., 2020; Ransbotham et al., 2017). Research on the adoption of new technologies also indicates that structural requirements for the organization as well as particular technical features have an impact on the adoption process. The issue of adoption has been examined from a variety of angles in the literature, including the individual, group, and organizational levels (Liu et al., 2008). Many studies are intended to evaluate individual attitudes and actions and to design methods best suited for forecasting individual adoption of technology (Oliveira and Martins, 2011; Liu et al., 2008). The Theory of Reasoned Action (TRA) (Ajzen, 1980), Theory of Planned Behaviour (TPB) (Ajzen, 1991), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Technology Acceptance Model (TAM) (Davis, 1985) are the commonly used theories.

The diffusion of innovation (DOI) theory by Rogers et al. (2014) and the technology-organization-environment (TOE) framework by Tornatzky et al. (1990) are the main theoretical foundations of research in the area of firm-level technology adoption (Chong et al., 2009;

Oliveira and Martins, 2011). DOI theory states that individual (leader) traits as well as internal and external organizational features influence how new ideas and technologies spread within a company and the success of technology adoption (Rogers et al., 2014; Bradford and Florin, 2003; Oliveira and Martins, 2011). On the other hand, the TOE framework (Tornatzky et al., 1990) describes how the acceptance and application of technical advances are influenced by three distinct kinds of factors: technology, organization, and environment (Baker, 2012). According to Baker (2012) and Henderson et al. (2012), the technical perspective focuses on the unique qualities and traits of technology, the organizational perspective emphasises organizational adoption-related attributes, and the environmental perspective is concerned with factors related to the surrounding environment. In other words, this theoretical framework groups these components into distinct constructs where technology adoption takes place, rather than offering a predetermined set of factors for the issue under analysis (Wang et al., 2010). Oliveira and Martins (2010) believe that compared with DOI theory, the TOE framework is completer and more comprehensive because it pays more attention to the environmental context. The application of AI in talent acquisition (Pillai and Sivathanu, 2020), intelligent robots in manufacturing firms (Choi et al., 2018), software services (Torres de Oliveira et al., 2019), the industrial Internet of things (Sivathanu, 2019), and Industry 4.0 in the Chinese automotive industry (Lin et al., 2018) have all been investigated using the TOE framework.

2.2.3.2 Organizational application of AI

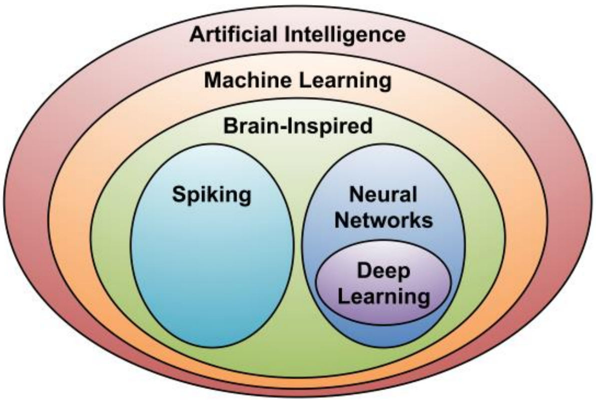
Firms' organizational and business processes are being radically transformed by AI and its associated techniques, including chatbots, neural networks, deep learning, machine learning, and virtual assistants (Kuzey et al., 2014). Indeed, AI has already completely changed how organizations are structured overall and interact with their surroundings (Jarrahi, 2018). Organizations now face a difficulty as well as a huge opportunity since AI has led to a new method of information processing; nevertheless, to take advantage of this potential, a shift in culture, attitude, and skill sets is necessary (Di Francescomarino and Maggi, 2020; Lee et al., 2018b). Technical advancements in AI have already had an impact on a wide range of industries and services, such as transportation (Falcone et al., 2007), health (Jiang et al., 2017; Koh and Tan, 2011), customer relationship management (Rubin et al., 2010), automatic email processing by virtual robots (Gabrilovich and Markovitch, 2009), and smart cities (Jain et al., 2004; Khashman, 2009; Srivastava et al 2017). When it comes to firm strategy, AI techniques have been explored to find new business partners (Mori et al., 2012), detect critical events to help with crisis management (Farrokhi et al., 2020), and construct socially responsible investment portfolios (Vo et al., 2019). AI can be implemented throughout the organization's whole value chain, integrating nearly every facet, owing to its numerous advantages in terms of innovation and prowess: research and development, maintenance, operations, sales and marketing, planning and production, demand forecasting, and services (Kuzey et al., 2014).

Management has a long history of research on AI applications in organizations (Haenlein and Kaplan, 2019). But academics and practitioners were not satisfied with the first notion of AI as cognitive systems that mimic human intelligence (Desanctis and Jackson, 1993; Huber, 1990). After fifty years, AI has advanced to support a range of complex tasks in organizations that once required human cognitive abilities, which include making decisions and judgements. The advancements have been made possible by the development of sophisticated algorithms, the growth of big data, and increased computing power (Mahroof, 2019; Shrestha et al., 2019; von Krogh, 2018). In contrast to earlier technologies, AI has a certain level of "intelligence" currently, such as the capacity for independent learning and action. As a result, it may develop a basic kind of "agency" in organizational structures and procedures (Kaplan and Haenlein, 2020). AI technique is now changing and reshaping how information is handled in firms due to its capacity to gather and store enormous data volumes. Organizational decision-makers may learn and improve their decision-making skills by using AI's information processing capabilities to assist in predictions, get new insights into emerging phenomena, and extract knowledge from vast volumes of data (Ghasemaghaei, 2018).

One of AI's most significant uses has been and continues to be organizational decision-making (Duan et al., 2019). A prior study conducted by the Boston Consulting Group with MIT Sloan Management Review revealed that 59% of the companies surveyed had an AI strategy in place, and 57% of them were piloting AI (Ransbotham et al., 2020). Meanwhile, a McKinsey survey revealed that 50% of the companies had implemented AI in at least one business function (McKinsey, 2020). AI has the ability to take on increasingly sophisticated jobs that involve cognitive skills, such as forming implicit judgements, feeling emotions, and driving processes, with the development of big data analysis tools and supercomputing information processing capabilities (Mahroof, 2019). This creates new application opportunities of altering the foundation of choices made by organizations (Aaldering and Song, 2020), and interest in AI applications is growing in all industries (Dwivedi et al., 2021). AI is thought to be able to "support decision-making and knowledge management, and automate customer interfaces" (Brock and von Wangenheim, 2019, p. 115), uncover hidden insights from data (Jovanovic et al., 2021), and assist employees in developing their analytical and decision-making skills as well as their creativity (Wilson and Daugherty, 2018). AI-based decision-making is thought to be more efficient, accurate, and adaptable (Agrawal et al., 2017; Metcalf et al., 2019).

From a technical perspective, the application of AI has mainly experienced a transformation from machine learning (ML) to deep learning (DL). Figure 2.1 well explains the relationship between AI, ML, and DL, that is, ML is a huge branch under AI, and DL is a subset of ML (Sze et al., 2017). Arthur Lee Samuel first used the term "machine learning" in 1995 (Syam and Sharma 2018). A lot of data is needed for machine learning (ML), which is often seen as a need before creating AI applications (Castiglioni et al., 2021). It falls into one of two categories: unsupervised learning on unstructured and unlabelled data, or supervised learning on specified data that is examined to provide results (Syam and Sharma 2018). Without target variables, unsupervised ML can teach computers to find hidden patterns and structures (Lim et al. 2017). For instance, M6D employs this technology to show tailored advertisements for hundreds of firms in order to target potential customers (Perlich et al., 2014). In social applications, impression creation refers to the ability for marketers to target particular consumers as actual bidding transactions develop (Lee et al., 2018a). In order to calculate vast volumes of data on customer behaviour, make choices, and finally serve adverts in real-time, ML is essential to this process. Consequently, firms' sales management benefits from AI and ML (Syam and Sharma, 2018). While many argue AI and ML would lead to the elimination of employment, others think that by 2025, they will actually produce more than 2 million new jobs (Syam and Sharma, 2018). With ML, sales management may become very effective. Salespeople's job can be made easier by quick iterations of thorough reporting and service data, which enables firms to take identified patterns and trends into action. ML has the power to determine how long a patient should remain in the hospital in the context of healthcare (Daghistani et al., 2019). This advantage not only assists patients in making plans for their home care requirements, but it also gives hospitals the chance to make effective use of their facilities and staff (Bacchi et al., 2022). Additionally, according to Turgeman et al. (2017), ML may greatly increase hospital operation efficiency, which would enable medical facilities to treat more patients, schedule elective surgeries more effectively, and eventually support long-term strategic planning.

Figure 2. 1: Relationship between AI, ML, and DL (source: Sze et al., 2017)



DL algorithms are especially applicable to information processing in business as they excel at identifying patterns and producing precise predictions from unstructured data (such as pictures, text, and videos) (Hartmann et al., 2019). The backpropagation method is used by DL to tell the machine how to modify its internal structure. For example, by better processing and recognizing images, videos, and natural language, it outperforms ML in predicting potential drug molecules (LeCun et al., 2015). Moreover, the capacity of DL algorithms to provide several representations with high-level characteristics that reflect more abstract parts of the data makes them significant (Bengio et al., 2013). Since artificial neural networks (ANN) can carry out more complicated tasks than traditional neural networks, they are more often viewed as the representation for DL (Georgevici and Terblanche, 2019). The development of ANN has been facilitated by the widespread availability of cutting-edge technology, including commercial graphics processing units (GPUs), which accelerate ML calculations (Monroe, 2017). As a result, ANN is able to pick up information from what it observes to offer examples of things it has never encountered before. The network is made up of linked nodes and contains an input layer, an output layer, and one or more hidden layers (Lemley et al., 2017). In the business world, DL has gained a lot of traction in areas including supplier management, fraud detection, financial analysis, customer relationship management, and distribution channel management (Necula, 2017). Additionally, DL is often utilised to forecast financial issues using big data sets, such as risk management, construction portfolios, design and pricing security (Ozbayoglu et al., 2020). Financial modelling can also be completed more correctly using DL than with conventional programs (Heaton et al. 2017).

The ability of cognitive systems to observe, analyse, learn, and make judgements is a major source of inspiration for DL. By abstracting complicated issues using a hierarchical approach, DL speeds up the integration of AI into organizational decision-making (Najafabadi et al., 2015). DL applications are adding value in a number of different organizations. To improve decision-making and boost productivity, engagement, and employee retention, the human resource departments of global business leaders, such as Google, are using DL techniques (Davenport et al., 2010; Tambe et al., 2019). When attempting to enhance product and marketing choices, online merchants like Amazon and Alibaba often monitor and evaluate the purchase histories of user groups with DL techniques (Dawar and Bendle, 2018; Kaplan and Haenlein, 2020). Additionally, it seems that the use of DL is expanding quickly beyond big companies to include various types of organizations (Kaplan and Haenlein, 2020). DL is used in a variety of sectors, such as banking, retail, energy, insurance, healthcare, and transportation (Balducci et al., 2018), with the goal to enhance overall organizational performance (Wang and Hajli, 2017; Yang et al., 2015).

At the nontechnical level, scholars and practitioners have also had many valuable discussions on the factors that influence successful use of AI technique by organizations. According to Brock and Von Wangenheim (2019), the application of AI is often a part of a company's digital transformation initiative. AI is not used in isolation but as a technical element of several technologies designed to enhance the company's current and future operations. In other words, AI initiatives often take place in the context of digital transformation (Brock and von Wangenheim, 2019). They further establish a DIGITAL (data, intelligence, being grounded, integrated, teaming, agility, and leadership) guideline for digital transformation leaders to better apply AI approaches based on this concept and the empirical inquiry (Brock and von Wangenheim, 2019). According to Morikawa's (2017) analysis of more than 3,000 Japanese firms, there will be high expectations for the adoption and spread of AI techniques inside enterprises to boost revenue growth and increase productivity. Employee skills inside the organization and AI applications are complementary. Increasing the proportion of workers with high education degrees is one way to develop human capital, which is necessary to create value from new technology. Furthermore, firms operating in foreign markets have shown a favourable attitude about the influence of AI technique, suggesting that the advancement and spread of new technologies are complemented by increased globalisation of economic operations (Morikawa, 2017). According to some practitioners (Fountaine et al., 2019), recognising and minimising the organizational and cultural obstacles that AI projects face is essential to its effective integration in business. This entails weaning organizational members off of conventional modes of thinking, including depending too much on top-down decision-making which is incompatible with the sort of thinking needed for AI. Additionally, leaders may create effective AI initiatives by emphasising the projects' advantages and urgency, making significant investments in AI adoption and education, and considering the company's AI maturity, business complexity, and innovation pace (Fountaine et al., 2019). Firms must embrace an improved data ecosystem, which includes data governance, employing business-valued cases, analytical tools and technology, workflow integration, and an agile organizational culture, in order to effectively execute AI transformation (Bughin et al., 2017).

2.2.3.3 The impact of AI on organizations

The consequences of AI for managers and firms are still being studied (Liu et al., 2020; Paschen et al., 2020; Phan et al., 2017). Early studies have been conducted on AI-driven business models (Garbuio and Lin, 2019), AI-driven organizational decision-making (Shrestha et al., 2019), and strategies to build AI trust (Hengstler et al., 2016). The literature on practice-oriented management (Brock and Von Wangenheim, 2019; Davenport and Ronanki, 2018; Fountaine et al., 2019; Ransbotham et al., 2017; Tarafdar et al., 2019) often outlines the procedures and actions that managers may take to incorporate AI into their companies. Most agree that the impacts of AI extend beyond small-scale process improvements and include whole new approaches to running and expanding a firm. However, little has been done on how firms might use AI to gain new skills and switch to business models that are enabled by AI (Brock and Von Wangenheim, 2019; Iansiti and Lakhani, 2020). According to studies, the biggest obstacle to implementing AI is the absence of AIC (Brock and Von Wangenheim, 2019). Further research into the nature of these organizational capabilities appears reasonable.

Numerous studies support AI's beneficial effects on organizations (Björkdahl, 2020). AI has affected business models and permeated a number of sectors (Brynjolfsson and McAfee, 2017; Davenport and Ronanki, 2018; Hoffman, 2016). These studies see AI as a tool that facilitates paradigm shifts in business processes, and changes in business models brought about by technical innovation are fraught with uncertainty (Hess et al., 2016). According to research, AI may alter team relationships (Lawler and Elliot, 1996; Shukla, 2016), capacity development (Gaines-Ross, 2016), and strategy work (Agrawal et al., 2017; Anandarajan, 2002).

Furthermore, the complementary role of AI in management tasks such as decision-making has changed the source of corporate competitive advantage (Krakowski et al., 2023). Key stakeholders will probably learn more about the advantages and disadvantages of AI as it becomes more widely used (Li, 2010; Wellers et al., 2017). Actually, firms are putting a lot of effort into learning how to foresee and investigate novel applications of AI solutions (Wellers et al., 2017; Yeomans, 2015).

Customer demands must be the basis for any value produced by digital technology (Gebauer et al., 2005; Gerpott and May, 2016). AI may be very important in the configuration of new, cutting-edge goods and services in terms of value generation (Haug et al., 2012). Research shows that firms may use AI approaches to broaden their product and service offerings, which enables them to discover new markets (Cenamor et al., 2017; Hasselblatt et al., 2018). Additionally, firms may employ digital technology to lower transaction costs, enhance offerings, and respond to consumer needs (Gerpott and May, 2016; Laudien and Daxböck, 2016). Previous studies also look at how AI propels innovation and provide recommendations for how firms may generate new value from their goods and gain specific competitive advantages. Manufacturing companies, for instance, may automatically react to unforeseen occurrences like machine breakdowns and quality flaws by employing AI techniques to access real-time and historical data (Tao et al., 2018; Li et al., 2019). Furthermore, since AI can provide goods that approach mass manufacturing efficiency while meeting the requirements of individual customers, it is well-positioned to enable mass customisation (Jiao et al., 2007). To create more individualised products and services, information on user demographics, preferences, and behaviours may be gathered from many sources and accurately measured using AI (Tao et al., 2018). This gives manufacturers the opportunity to broaden their product and service offerings via customer-centric or intelligent design. Studies conducted on the manufacturing sector also demonstrate that companies can enhance their comprehension of clients, rivals, goods, machinery, procedures, services, workers, suppliers, etc. by merging AI technique with cutting-edge technologies such as cloud computing and the Internet of Things to gather, store, process, transfer, visualise, and utilise data (Jiao et al., 2007; Tao et al., 2018). For instance, by improving customer order monitoring and tracing and more effectively integrating value chain operations, digital procurement systems based on AI approach benefit manufacturers, suppliers, and consumers at the same time (Björkdahl, 2020). Throughout the product life cycle and manufacturing value chain, a lot of data may be collected and analysed (Tao et al., 2018). AI also offers customization-driven advantages in B2B settings, assisting companies in offering specialised items to their clients (Mishra et al., 2020; Zhang and Xiao., 2020).

The impact of AI is also intuitively reflected in organizational performance. On the operational side, managers utilise expert systems to lower uncertainty about demand, capacity, and supply availability (Chen et al., 2015; Dubey et al., 2019). AI techniques also help organizations analyse and combine complicated information from a range of sources. Consequently, by developing new goods or services, raising the quality of existing offerings, cutting expenses, and lowering the market risks associated with new product development, AI-supported dynamic capabilities help firms enhance their operational performance (Dubey et al., 2020). The primary factor driving the value of AI solutions is increased efficiency (Mikalef et al., 2023). AI boosts productivity in marketing by using chatbots to take the place of sales and customer service representatives, enhancing salespeople's performance by giving them extra information and analysis in real time during calls (Bharadwaj and Shipley, 2020; Davenport et al., 2020), or mentoring salespeople directly (Luo et al., 2021). According to Luo et al. (2021), chatbots outperform the unskilled staff when it comes to making highly organised outbound sales calls. Nambisan et al. (2017) and Yoo et al. (2012) find that AI also has a significant influence on organizational innovation and research and design (R&D) activities. According to Liu et al.'s study (2020), AI fosters technological innovation in organizations via four distinct channels: knowledge generation, knowledge spillover, learning capacity, R&D and talent investment. AI changes how R&D work is carried out and structured (Cockburn et al., 2018), creates new issues (Haefner et al., 2021), and compels innovation processes to critically examine the pillars of current product and service portfolios (Nylén and Holmström, 2015). AI is stressing the network impacts of data in the R&D process as firms are driven to enhance their capabilities to interchange, integrate, and analyse digital information across products, units, and organizations (Gregory et al., 2021). In particular, AI may be used to gather data on consumer needs, product use, and process performance in new ways throughout the innovation, and then evaluate and reorganise the data (Burström et al., 2021; Trocin et al., 2021). The potential of AI to investigate data and provide suggestions for innovation, as well as how it will improve strategic decision-making and facilitate creative business solutions, is yet largely unexplored in research (Keding and Meissner, 2021; Leyer and Schneider, 2021). The way AI is implemented in R&D will rely on innovators' technical mentality and aptitude (Holmström, 2021; Solberg et al., 2020), for example, how they shift perspectives on the kinds of innovations that organizations and industries need to make (Lyytinen, 2021). Lastly, a limited number of research have also looked at the connection between AI and the global performance of firms. Prior research has shown that digital technology may serve as a catalyst for a company's global development (Jean et al., 2010; Sinkovics et al., 2013). Firms now have new resources at their disposal for organising economic activity and commercial operations, as well as new tools and techniques for connecting with and serving global consumers (Falahat et al., 2020). AI has the ability to significantly increase decision-making efficiency when evaluating the prospects of foreign markets (Martinez-Lopez and Casillas, 2013; Neubert and Van der Krogt, 2018). The correlation between export intensity and AI readiness, and the favourable association between a firm's worldwide success and its mastery of AI knowledge, are further confirmed by Denicolai et al.'s (2021) research.

On the other hand, AI does not always bring positive impacts to organizations (De Bruyn et al., 2020). Most of the past research focused on the importance of AI and the advantages it creates (Makridakis, 2017; Fragapane et al., 2022), including discussions on how AI can benefit firms and make profits (Basri, 2020). However, some research has proven that the announcement of investment in AI will lead to a decline in the company's market value (Lui et al., 2022). Empirical evidence has also verified that the opacity of AI technique will lead to problems such as reduced decision-making quality and increased risks, which will cause a series of adverse consequences such as low operating efficiency, negative sales growth, and employee dissatisfaction, ultimately leading to a competitive disadvantage for the firm (Rana et al., 2022). In addition, two characteristics that might have a detrimental influence on the quality of relationships have been found by marketing research. One is the lack of trust (Morgan and Hunt, 1994), which may impact both B2B and B2C settings (Chang and Chen, 2008; Kingshott et al., 2018; Palmatier et al., 2006). The other is asymmetric power, whereby firms with strong AI capabilities may extract more consumer insights than others, thus giving them a larger degree of power (Chen et al., 2017). Even in cases when the dominant party does not misuse its influence, the very existence of power imbalances may foster an environment where the weaker parties worry about being taken advantage of, which lowers their level of trust (Geyskens and Steenkamp, 1995).

Customers' worries about privacy, prejudice, and disdain for individuality are among the trust-related issues that AI customisation brings up (Granulo et al., 2021; Guha et al., 2021; Longoni et al., 2019; Puntoni et al. 2021). First, AI makes it possible to get insights into client data, which might raise issues with privacy (Guha et al., 2021). This data and associated analysis may be considerably more harmful in the case of a data breach (Labrecque et al., 2021). Second, the use of AI has also heightened concerns about bias. AI solutions have been criticized as being a black box, which may generate lower levels of trust and consequently less adoption and participation (Rai, 2020). Third, it is possible that AI lacks empathy and so fails to correctly consider the distinct identities, situations, and preferences of each client (Granulo et al., 2021; Longoni et al., 2019). According to Longoni et al. (2019), consumers are less likely to accept healthcare choices offered by AI. Additionally, consumers value human work above robot-produced goods, indicating that human labour is more unique to them (Granulo et al., 2021). For firms, significant efficiency gained from AI may lead to power asymmetries, which may subsequently have a negative impact on weaker exchange partners (Villena and Craighead, 2017). A simple example is the relationship between Amazon and its third-party sellers who sell directly on it. Amazon has powerful AI capability to analyse customer data and generate deep insights (Cao, 2021). Amazon may use this information to create terms and conditions of trade with third-party sellers that would be helpful to its own direct sales and detrimental to third-party sellers (Bloodstein, 2019). To put it another way, Amazon may better forecast demand and make sure that a comparatively higher percentage of sales to a more lucrative clientele go via Amazon as opposed to other parties.

2.2.4 Research on AI in business and management

2.2.4.1 The nontechnical and technical research streams

Through the researcher's previous systematic literature review (SLR) on AI research in the business and management field (Cui et al., 2022), it is found that there is a huge divergence which cannot be ignored between nontechnical and technical research. Specifically, when scholars conduct research on AI technique and/or its applications, a common problem is that they either only focus on technical development rather than proving its utility or assessing the impact (e.g., Feng and Zhang, 2022; Machuca et al., 2012), or discuss impacts and solution strategies but ignore specific AI techniques due to a lack of technical knowledge (e.g., Brooks et al., 2020; Grewal et al., 2017). Based on this divergence, the researcher uses one of the largest literature databases (Aghaei and Salehi, 2013), Web of Science, to look up the research in this area for review. The 2021 Academic Journal Guide (AJG) produced by Chartered Association of Business Schools (CABS) is referred to, with journals whose quality ratings are

3 or above considered. Meanwhile, due to the rapid development of AI technology, the iteration and timeliness of techniques are also factors worth considering (Dwivedi et al., 2021). Therefore, the researcher takes the concept of “Enterprise 2.0” proposed by McAfee (2006) as a starting point and mainly reviews AI research after 2006.

In the process of reviewing AI research in this field, the researcher found clear characteristic differences between nontechnical and technical research (Cui et al., 2022): 1) Most nontechnical papers explicitly draw on a wide range of business and management (B&M)-related theories (e.g., Prentice et al., 2020). 2) Nontechnical research often provides clear managerial implications, even if these implications are generated through technical innovations (e.g., Priore et al., 2019). 3) The focus of technical research is only on technical progress and the application of mathematical/programming methods, and it only provides scientific results without any direct reference or contribution to management theories (e.g., E.-Nagy and Varga, 2022). 4) Technical researchers emphasize the improvement, performance, and advantages of the AI algorithms/models they propose (e.g., He et al., 2014), while nontechnical researchers regard AI as a means to effectively implement strategic goals, and demonstrate its value maximization and implications in business and management (e.g., Mori et al., 2012). Therefore, the researcher believes that B&M research on AI can be distinguished by nontechnical and technical characteristics.

2.2.4.2 Divergence between the two streams

Through further review, it is found that there are many differences between B&M scholars' nontechnical and technical research on AI, including conceptual understanding, research focus, research theory, research methods, etc. These divergences in each aspect are discussed in detail below.

Conceptual divergence

Nontechnical research and technical research have different ways of understanding and defining AI. For nontechnical research, the most common approach is to refer to established AI concepts from various sources. Among these sources, the main ones adopted include several definitions already discussed in chapter 2.1: 1) computer scientists Russell and Norvig's (2016) four types of definitions of AI systems - thinking/acting like humans or thinking/acting rationally; 2) one of the founders of the AI discipline, John McCarthy's emphasis on machine behavioural intelligence (McCarthy, 1959; McCarthy et al., 2006); 3) management scholars Kaplan and Haenlein's (2019) elaboration on the main functions of AI and the necessary connection between AI and data. Additionally, since there is no unified definition of AI (Wang, 2019), many nontechnical researchers also choose to define the term in their own words without referring to any existing sources (e.g., Kumar et al., 2019; Longoni et al., 2019).

In contrast, few technical papers provide a clear AI definition. This may be because most technical research focuses on specific AI techniques, such as natural language processing (Reisenbichler et al., 2022), deep learning (Shrestha et al., 2021), optimization algorithms (Tsafarakis et al., 2013), etc. They provide detailed introduction to the ideas and development of these technologies. Research will explain only if it is relevant to the general concept of AI. In this case, the author usually cites existing information rather than giving his or her own understanding, because the concept of AI is not the main focus of the paper.

In fact, although nontechnical researchers actively cite definitions from the technical side (such as Russell and Norvig (2016)), popular definitions from the nontechnical side do not appear in the technical literature (such as Kaplan and Haenlein (2019)). Nontechnical academics seem to be more focused on building up conceptual understanding of AI first. However, technical research tends to believe that AI is a well-known term and does not consider it necessary to explain it conceptually.

Research focus divergence

Technical research on AI mainly focuses on optimisation and production (Fragapane et al., 2022; Zhang et al., 2017), prediction and diagnosis (Lamperti and Zhao, 2014; Smiti and Soui, 2020), intelligent system design (Garcia et al., 2006; Penharkar, 2007), information processing (Dai et al., 2022), and other aspects. Technical research covers the development and progress of various branches of AI techniques. These techniques specifically include: ANN, decision support systems, case-based reasoning, expert systems, classifiers, etc. Existing research has applied AI techniques to many prediction and pattern recognition problems. For example, Hain et al. (2022) integrate natural language processing with nearest-neighbour approximation to examine the technical similarity between patents and establish a patent connection network. Li et al. (2019) study the feasibility and performance of ANN in predicting crude oil prices and confirm that ANN-based AI models are promising tools for crude oil price analysis and prediction. The predictive capabilities of AI technique have also been further extended to a wider range of business areas. For instance, short-term stock prices (Chan Phooi M'ng and Jer, 2021), product sales (Sohrabpour et al., 2021), supply chain customer demand (Pereira et al., 2022a), and even business failure (Bose and Pal, 2006) can all be predicted by ANN.

In contrast, nontechnical research mainly discusses AI adoption and its possible impacts at different levels: individuals (e.g., Beeler et al., 2022; Fossen and Sorgner, 2022), organizations (e.g., Fountaine et al., 2019; Asatiani et al., 2021), and society (e.g., Hermann, 2022; Tiberius et al., 2022). Different views on the advancement of AI techniques can also be seen in the nontechnical literature. Taking the healthcare industry as an example, the AI-related applications in the medical field have developed rapidly (Johnson, M. et al., 2022; Youn et al., 2022), which has provided great help for resource utilization and patient services (Yang et al., 2010). However, the collection, storage, use, and sharing of data that underlie AI have triggered discussions among management scholars on issues such as user acceptance, governance, quality, security, standards, and privacy (Dwivedi et al., 2021). Longoni et al. (2019) investigate consumer acceptance of medical AI and propose interventions to improve its acceptance. Pan et al. (2019) explore the influencing factors of doctors' willingness to adopt smart medical services from the perspective of technology transfer. Furthermore, Fan et al. (2020) propose a model to understand the acceptance behaviour of medical professionals towards AI-based medical diagnosis support systems. These studies demonstrate that while technical researchers work on developing AI-based healthcare techniques, nontechnical management scholars struggle to find ways to use these techniques rationally and effectively.

Another point worth noting is that the literature generally does not believe that AI can completely replace humans (De Cremer and Kasparov, 2021), but nontechnical and technical research also discuss this point in different ways. Research seems to recognize the inevitable limitations of fully deploying automation (Raisch and Krakowski, 2021) and emphasizes a more realistic concept of human-centric AI (Rožanec et al., 2023; Harfouche et al., 2023). Based on this, one of the focuses of technical research is to train AI to learn the way humans think and behave, so that technical progress can better serve humans (Chen et al., 2021).

Humans may move to the higher end of the industrial production chain, such as focusing on activities related to the design and integration of intelligent systems composed of machines, technology, and human labour (Grønsund and Aanestad, 2020). Accordingly, nontechnical research is based more on management theory and discusses in detail the role of AI in business and organizations as well as its impact on human work (Giuggioli and Pellegrini, 2022; Hunt et al., 2022; Margherita, 2022; Truong and Papagiannidis, 2022).

Theoretical divergence

A notable and reflective finding is that there is no literature that applies specific management theories in technical studies. Technical researchers often introduce the development and deficiencies of the AI techniques they study in detail, but fail to fully demonstrate the needs and impacts in the application field. In nontechnical papers, especially some conceptual ones, researchers have begun to pay attention to and understand specific AI techniques and have made clear explanations in the articles (De Bruyn et al., 2020; Kumar et al., 2021). This will allow readers (probably also from nontechnical fields) to better understand these technologies and why these AI techs would have a profound impact on the discipline/industry. Technical research may focus much on the development of AI algorithms and models themselves. That is to say, its focus is to prove that the algorithmic model developed or proposed are superior to other similar ones' performances.

In fact, management and organization studies have a very rich body of theories to apply. In nontechnical literature, organization-level theories include organizational learning theory (e.g., Wijnhoven, 2022), organizational information processing theory (e.g., Benzidia et al., 2021), innovation-related theories (Liu et al., 2020), resource-based view (e.g., Dubey et al., 2021), and more, helping to study the strategies organizations adopt and the corresponding impact when applying AI techniques. Individual-level theories are mainly used to study individual attitudes, behaviours, and human-computer interaction situations when faced with AI applications. Researchers tend to study such topics using trust theory (e.g., Gillath et al., 2021), uncanny valley theory (e.g., Stein et al., 2020), technology acceptance theories/models (e.g., Lu et al., 2019), anthropomorphism (e.g., Li and Sung, 2021), consumer-related theories (e.g., Tassiello et al., 2021), etc. In addition, some studies are also based on theories at the contextual level, such as institution theory (Bag et al., 2021) and sociotechnical theory (Makarius et al., 2020). This group of research is mainly related to the impact and critical success factors of AI applications considering the effects from industry, government, and the society. The diversity and solidity of theories utilized explain why nontechnical literature often includes a chapter of theoretical foundations or literature review, with the theoretical contribution of the research at the end. Technical literature, on the other hand, often only reviews state of the art in the specific AI technique and discusses the contribution of the research to technical development.

Methodological divergence

The methods of nontechnical research are diversified, mainly conceptual and empirical research. The technical research method is relatively more “monotonous”, and more than 90% of the technical research adopts the method of modelling and simulation. In contrast, conceptual and empirical research are the main methods for nontechnical literature. In conceptual research, scholars would discuss the impact of AI applications on disciplines and industries through existing research and theories, as well as future research directions (e.g., Huang and Rust, 2021; Syam and Sharma, 2018). A large amount of qualitative and quantitative research also complement these discussions with a wealth of empirical evidence and offers many insights based on empirical data. Meanwhile, a considerable part of marketing research uses experimental methods when studying consumer psychology and behaviour, by setting specific experimental situations and conditions to observe the subjects’ reaction (e.g., Whang and Im, 2021). However, for the technical literature, modelling and simulation has become the method of most research. Technical research often establishes an algorithmic model first, and then proves the validity of the model by inputting various data and investigating results. Regarding the simulation, about half of the research is based on empirical data from the real world. Scholars sometimes call it "experimental simulation", in which case simulation can be understood as a substitute for experiment (Guala, 2002). The other half of the studies are validated using a set dataset or scenario. In short, these studies are completed by means of machine computing. There is only a very small amount of research that qualitatively or quantitatively determines the effectiveness of AI techniques through empirical studies (e.g., Piris and Gay, 2021).

To conclude, obvious divergences exist between technical and nontechnical aspects in AI research in the B&M fields. This demonstrates that due to the complexity AI concept, there are disciplinary boundaries or differences between its relevant research. This phenomenon means that such differences need to be noted in subsequent research, and the knowledge related to AI cannot be generalized for now. Meanwhile, it is necessary to strengthen interdisciplinary cooperation and try to more systematically promote exchanges between AI researchers with technical and nontechnical backgrounds. Besides, few attempts have been made to systematize and comprehensively theorize the development of the AI concept and its interdisciplinary impact (Csaszar and Steinberger, 2022). Particularly, how to effectively integrate the specific techniques into traditional theories and existing knowledge systems in the B&M fields remains to be an unsolved issue (Baum and Haveman, 2020; Berente et al., 2021).

These findings are also the reason why the researcher discusses the characteristics and usage of AI mainly from a technical perspective in chapters 2.2.2 and 2.2.3. Moreover, these findings have also become an important motivation for the researcher to conduct follow-up research, that is, on the basis of paying attention to both technical and nontechnical features of AI, to contribute to the integration of AI-related concepts and impacts as well as management theory in AI research.

2.3 Artificial intelligence capability (AIC)

The ability of a firm to use, combine, and integrate its organizational resources in order to accomplish desired outcomes is known as organizational capabilities (Dosi et al., 2000; Kogut and Zander, 1992). According to Peppard and Ward (2004), capabilities result from the intricate interplay of resources within the context of organizational roles, structures, and procedures. Organizations place a higher value on these intangible qualities than on concrete resources like information technology (IT) or human resources (Dosi et al., 2000; Kogut and Zander, 1992). As IT becomes increasingly important to organizations, information systems (IS) scholars have studied the role of IT on organizational capabilities. For one thing, the use of IT enables specific organizational capabilities (Gupta and Goerge, 2016). For another, organizational capabilities are required to create value from IT (Ravichandran et al., 2005).

Before the concept of AIC appeared, many scholars had studied the capabilities required by organizations to use IT and demonstrated their measurement methods and functions, such as technological capabilities (Rush et al., 2007; Stuart and Podolny, 1996), IT capabilities (Bhatt and Grover, 2005; Santhanam and Hartono, 2003), IS capabilities (Aydiner et al., 2019), big data analysis capabilities (BDAC, Akter et al., 2016; Gupta and Goerge, 2016), etc. These capabilities are linked to IT value generation and organizational performance, according to theories and empirical evidence (Aral and Weill, 2007; Bharadwaj, 2000; Mithas et al., 2011). Citing Bughin et al. (2018), Cox (2022) suggests that the following constitute AI capability: computer vision, machine learning, robotic process automation, natural language text understanding, virtual agents or conversational interfaces, autonomous vehicles, natural language generation, natural language speech understanding, and physical robotics. This is essentially a technical interpretation of the AI notion. Some recent studies have also developed dimensions of organizational capabilities related to AIC. For example, Gupta et al. (2020) regard technological capabilities, marketing capabilities, human resource capabilities, and firm agility as the relevant capabilities of a firm using digital analytics. Bag et al. (2021) proposed that tangible resources (i.e. big data management infrastructure, technical resources) and workforce skills are the core resources for firms to implement AI based on RBV. Jaiswal et al. (2022) believe that improving employees' data analysis, digital, complex cognitive, decision making, and learning skills is the necessary condition for organizations to fully utilize AI to create competitive advantages.

Earlier studies on organizational resources required for AI deployment mostly addressed the corresponding organizational variables (Enholm et al., 2022; Jöhnk et al., 2021; Mikalef and Gupta, 2021; Mikalef et al., 2021; Nam et al., 2020; Pumplun et al., 2019). According to research, firms require certain human skills and roles (Anton et al., 2020), a strong relationship between AI and business units (Jöhnk et al., 2021), an experimental and data-driven culture (Fountaine et al., 2019), and a sufficient quantity and quality of data (Pumplun et al., 2019). These resources are linked to more effective AI deployments and value generation for organizations. For instance, Mikalef and Gupta's study (2021) shows how AI-related resources might enhance organizational creativity and performance. However, these resources do not provide value on their own (Peppard and Ward, 2004). Dosi et al. (2000) and Kogut and Zander (1992) find it more crucial to take into account the organizational capabilities that result from the usage, integration, and combination of the specified resources. Sjödin et al. (2021) provide three organizational capabilities—data pipelines, algorithm development, and AI democratization—that might propel the innovation of AI business models. Unfortunately, since their study only focuses on digital servitization, it cannot be broadly applied (Sjödin et al., 2021). To solidify and expand the idea of organizational capabilities in the context of AI, further study is required (Mikalef and Gupta, 2021; Sjödin et al., 2021). To be more precise, it is still unclear how certain skills address the special features of AI and help to implement it, which can explain why these capabilities are necessary in the context of AI. The author goes into more depth on this in section 3.3.

2.3.1 Definition of AIC

Organizations must create a data-driven culture and integrate business analytics with organizational culture across the whole company in order to reap the full benefits of AI (Carillo et al., 2019). Mikalef and Gupta (2021, p.4) define AIC as "the ability of a firm to select, orchestrate and leverage its AI-specific resources". Three dimensions—tangible, human, and intangible resources—can be used to conceptualise the AIC components (Mikalef and Gupta, 2021). This conceptualization is consistent with Grant's (1991) classification of the types of resources that drive organizational capabilities for performance, which separates tangible resources (e.g., material and financial), human skills (e.g., knowledge and skills), and intangible resources (e.g., strategic orientation). No single one of these aspects is able to solely convey what an AI capability is. Since the AIC constructs are relatively wide and have little overlap, the three primary dimensions cover the facts of the whole capability (Mikalef and Gupta, 2021). Previous studies demonstrate that developing distinctive competencies brings firms performance boost and competitive edge (Gupta and George, 2016). This definition is founded on the idea that organizational considerations are just as crucial to the use of AI as its technical aspects. By reviewing prior research and speaking with practitioners, the three dimensions are determined (Mikalef and Gupta, 2021). Using Mikalef and Gupta's (2021) paradigm, the primary aspects of AIC may be identified. Data, technology, and basic resources constitute tangible resources included in the framework. Technical and business skills make up human resources. Intangible resources are categorised into risk proclivity, organizational change capacity, and interdepartmental coordination.

Tangible resources

According to Wernerfelt (1984), tangible resources are those that can be purchased or sold in a market, such as financial and physical assets like debt and equity as well as facilities and equipment. Krakowski et al. (2023) argue that these resources are largely accessible to all firms operating in the market and are not thought to provide them a competitive edge. They are nevertheless required, despite the fact that they are insufficient on their own to produce capabilities (Mikalef and Gupta, 2021). Three dimensions are distinguished among tangible resources:

Data

The vast disparities in capabilities across firms using AI result from their disparate data gathering strategies (Ransbotham et al., 2017). Since quality data is needed to train AI systems, its availability is seen to be essential to the application of AI (Mikalef and Gupta, 2021). Firms now have more ways to process consumer data than ever before because to the big data revolution and improved computer power (Vieira and Sehgal, 2018). However, Quan and Sanderson (2018) note that one of the three main difficulties in managing the AI ecosystem is data collecting. The primary obstacles to implementing AI in the public sector, according to Wirtz et al.'s (2019) analysis of 17 issues, are system/data quality and integration. One of the main challenges in applying AI is to store, organise, and create views of unstructured data in a cost-effective way. Successfully leveraging data is crucial to enhance AI usage, according to a study on how banks can better serve customers through AI (Vieira and Sehgal, 2018). Firms may now get data in a variety of forms and from a variety of sources (Kersting and Meyer, 2018). Diverse limitations happen to organizations concerning data volume, granularity, integration, access, inter-organizational exchange, and processing (West et al., 2018).

Technology

Another primary obstacle to the implementation of AI, according to a McKinsey assessment, is technological infrastructure (Chui and Malhotra, 2018). Having the right infrastructure in place is essential when using massive, unstructured, dynamic, and complicated data sources to develop AI systems (Mikalef and Gupta, 2021). Firms now need increasingly sophisticated technology to handle, store, transfer, and secure data in order to develop AIC. This covers every stage, from gathering data to using it. The volume, format support, and scalability of the storage infrastructure needed will depend on the particular demands, since data requirements may impact the scope and nature of AI initiatives (Bayless et al., 2020). Various technological infrastructures are needed for AI endeavours in order to create and handle data. For example, computer vision needs hardware that is particularly designed to handle image segmentation, object identification, pattern detection, and feature matching, as well as high-bandwidth networks and devices with built-in cameras that can capture pictures at high frame rates (Nixon and Aguado, 2019). Depending on the scope and nature of their AI initiatives, firms must also make investments in the development of enough processing capacity. Because AI necessitates the execution of intricate algorithms on massive volumes of data, which is also a crucial component of AI approach. Using GPU-intensive clusters and parallel computing is a usual way to get enough processing power (Nurvitadhi et al., 2017). Another common strategy is to use external cloud-based solutions to outsource the issue, as they are often less expensive than purchasing IT infrastructure (Kumar, 2016). Integrated cloud services, which enable sophisticated AI techniques to be applied via simple API (application programming interface) calls, have grown in popularity in recent years (Del Sole, 2018).

Basic resources

Time and money are the two main types of basic resources (Mikalef and Gupta, 2021). The second most prevalent issue with using AI, according to a Davenport and Ronanki (2018) survey of 250 executives, is the high cost of the equipment and knowledge required. Research by Wirtz et al. (2019) demonstrates one of the biggest obstacles to integrating AI is ensuring financial viability. Brynjolfsson et al. (2019) agrees that the AI adopters who have the least amount of adjustment costs will be the most successful ones. The aforementioned research together demonstrates that financial resources are a critical prerequisite for using AI. Yet, the majority of participants in the McKinsey survey said that less than 10% of their investment on digital technology was allocated to AI projects (Chui and Malhotra, 2018). Furthermore, it takes time for AI projects to pay off and provide the desired outcomes. Most efforts will need some time to develop before producing value, when most organizations are now experimenting with AI (Ransbotham et al., 2018). A sufficient amount of time resources must be planned and allotted for an AI initiative to succeed. Consequently, these resources constitute one of the dimensions on which AIC is formed, given the evident significance of time and funds as well as prior studies on IS business value (Gupta and George, 2016; Schryen, 2013; Wixom and Watson, 2001).

Human Resources

According to Boon et al. (2018), human resources are those that deal with an organization's human capital. This is often evaluated by looking at an organization's workforce's knowledge, expertise, leadership traits, vision, communication and teamwork skills, and problem-solving abilities (Bharadwaj, 2000; Ravichandran et al., 2005). Technical and business skills are essential components of human resources (Mikalef and Gupta, 2021). In other words, an organization's human AI resources should include crucial AI-specific talents. There are two aspects to human resources:

Technical skills

Technical skills are the abilities and expertise needed to supervise the implementation of AI algorithms, oversee the infrastructure needed for AI projects, and guarantee that AI applications accomplish their objectives (Mikalef and Gupta, 2021). One of the most often mentioned obstacles to employing AI techniques is a lack of experience. According to study by Alsheibani et al. (2019) of 207 organizations of different sizes, the most prevalent obstacle to deploying AI is a lack of skills for evaluating, developing, and implementing AI solutions. In another study, 35% of 250 executives agree that one of the biggest problems is finding enough AI experts (Davenport and Ronanki, 2018). Access to specialisation and experience is a significant problem, found by research on AI difficulties in the public sector (Wirtz et al., 2019). Expert algorithm developers may use the most recent advancements in AI to apply mathematical formulae that are abstract via hardware and software and turn them into recurring procedures (Spector and Ma, 2019). As was previously noted, AI incorporates a wide range of knowledge domains, including logic, mathematics, algebra, statistics, probability, and prediction. Furthermore, professional proficiency in language processing, programming, data structures, and cognitive learning theory are additional fundamental AI technical capabilities (Lesgold, 2019). The AI age will see the emergence of three critical roles: trainer, explainer, and maintenance (Wilson et al., 2017). Maintainers make sure AI systems function as intended and handle any unanticipated repercussions. Trainers teach AI systems. Explainers explain the inner workings of AI to nontechnical audiences. Despite their scarcity at the moment, these abilities are expected to become more prevalent over time due to the growth of online learning and higher education, eventually becoming commercial resources that firms may use (Wilson et al., 2017).

Business skills

Managers' ability to perceive and anticipate business difficulties, effectively direct AI programmes, make use of resources, coordinate AI-related activities, and overall exhibit strong leadership to assist AI initiatives is referred to as business skills (Mikalef and Gupta, 2021). In-depth interviews with over 30 technical experts and executives, as well as a global survey of over 3,000 executives, managers, and analysts across industries conducted by Ransbotham et al. (2017), reveal that many leaders are unclear of what they expect from AI and how to incorporate it into their business models. The research also reveals that executives of companies with successful AI programmes often have a better grasp of what is required to put AI into practice. Successful companies also create strict business plans for AI projects and get support from top leadership (Ransbotham et al., 2017). One major obstacle to the use of AI is a lack of administrative assistance (Alsheibani et al., 2019). Companies' understanding of AI applications is constrained (West et al., 2018), and many have trouble locating appropriate tools and use cases for the application domains they are involved in (Schlögl et al., 2019). According to Davenport and Ronanki (2018), managers' lack of knowledge of cognitive technologies would also hinder the use of AI. To be successful, AI projects need leaders to have a sincere knowledge of the issues and be willing to make significant adjustments. Nonetheless, it is found that a third of managers are ignorant about the operation of AI techniques (Davenport and Ronanki, 2018). Managers must become proficient in AI methodology and its possible applications in various organizational areas in order to effectively lead AI efforts (Mikalef and Gupta, 2021). The ability to plan and begin AI deployment is especially important when there is a strong force inside the organization opposing change because AI causes a danger to replace the tasks now done by human workers (Huang and Rust, 2018). Managers must foster positive connections between technical and nontechnical employees in order to prevent implementing AI too late and reducing economic value (Enholm et al, 2022). The capacity to use AI techniques to manage organizational transformation and seize opportunities may make an organization distinctive and challenging for others to copy (Helfat et al., 2023).

Intangible Resources

According to Hall (2009), intangible resources are those that are highly valuable in an unpredictable and dynamic market and are challenging for other organizations to duplicate. Intangibles are much more elusive and harder to locate inside organizations than the other two resources (Surroca et al., 2010). There are three categories for intangible resources:

Inter-departmental coordination

Successful multidisciplinary projects are based on the capacity of various organizational components to coordinate work and share a common vision (Kahn, 2001). Inter-departmental coordination is characterised by high levels of shared values, dedication to shared objectives, and cooperative conduct (Mikalef and Gupta, 2021). Maintaining continuous links across departments is beneficial (Kahn, 1996), and interdepartmental cooperation has long been acknowledged as a critical factor in fostering innovation and creativity inside companies (Evanschitzky et al., 2012). According to research on AI and commercial value, companies need to foster a culture of cooperation, shared objectives, and resource sharing in order to fully realise the potential of AI technology (Ransbotham et al., 2018). Fountaine et al. (2019) find that cross-functional teams with a variety of backgrounds and viewpoints work together to build AI with the highest potential for impact. By doing this, it will be ensured that AI projects target wider organizational goals rather than just discrete business issues. Organizations may improve the overall performance of deployed AI systems by fostering multidisciplinary teams, which better prepare them to think through the operational problems of new applications (Fountaine et al., 2019). A common language and understanding among staff from various departments would also lessen the need to introduce new AI applications or modify current ones, which might make companies more flexible and adaptive when implementing AI applications (West, 2018). Additionally, studies show that since they impede the creation of end-to-end solutions, functional silos represent one of the biggest obstacles to reaping the benefits of AI projects (Chui and Malhotra, 2018).

Organizational change capacity

To properly use AI, business models must be modified (Quan and Sanderson, 2018). In line with this, business value creation will also alter (Enholm et al., 2022). Changing current business procedures and turning tacit knowledge—such as insights acquired from them—into a competitive advantage is one of the biggest difficulties facing firms today (Vieira and Sehgal, 2018). It takes work and entrepreneurship to complement AI approach in order to realise its advantages (Dubey et al., 2022). Adaptability to restructuring at the individual, organizational, and societal levels is also necessary (Brynjolfsson et al., 2019). One of the major issues encountered by AI projects (Davenport and Ronanki, 2018; Wirtz et al., 2019) is the ability to integrate AI method with current processes and systems, which is included in organizational change capacity (Mikalef and Gupta, 2021). In many respects, such an integration process is challenging. First, integration could need significant adjustments to a number of interconnected processes and systems depending on organizational structures and modules (Moşteanu, 2020). Moreover, these modifications are often implemented in tandem with continuing business activities, which may cause disruptions to current systems and processes that are essential to the running of the organization (Shrestha et al., 2019). Additionally, data from many systems must be integrated, which may be a challenging procedure if the data is not well-structured and organised (Bhima et al., 2023). The ability to overcome opposition from people and convey change is another aspect of organizational change capability (Mikalef and Gupta, 2021). Numerous issues have been raised and will continue to be posed by the advancement of AI techniques (Dwivedi et al., 2021). Employees' opinions towards AI vary these days, therefore it's crucial to take into account whether or not they are willing to work with AI (Li et al., 2019). Organizations do not claim that they must lay off employees in order to use AI techniques, but the latter may be reluctant to embrace AI due to fear of losing their jobs (Schlögl et al., 2019). A survey shows firms are more worried about opposition from people than technical issues with AI (Schlögl et al., 2019). According to Alsheibani et al. (2019), employees' lack of faith in AI, fear of change, fear of ineptitude, fear of losing significance, and fear of losing their jobs are the main causes of this resistance.

Risk Proclivity

According to a survey of leaders from different nations and sectors, firms that approach new initiatives with a greater emphasis on risk reap the rewards sooner than their opponents (Ransbotham et al., 2018). Risk proclivity has many different meanings in management (e.g., "risk-taking strategic orientation", "proactive stance," etc.) and is related to reflective proactiveness and proactive change typologies of scenarios (e.g., prospectors) (Avlonitis and Salavou, 2007; Sambamurthy et al., 2003). Proactive behaviour and taking risks are often linked to increased levels of innovation production and market leadership (Salavou et al., 2004). Ransbotham et al. (2018) observe that in the context of AI, firms which have a strong commitment to AI efforts and accept risk propensity often outperform competitors who are hesitant to make such commitments. According to Fountaine et al. (2019), organizations need to move away from risk-averse tactics and adopt more experimental, agile, and flexible practices. In conclusion, research indicates that firms with a high risk tolerance may be the first to use AI and benefit from it, giving them a competitive advantage.

2.4 Antecedents for firm's AIC

According to Mikalef and Gupta's (2021) conceptualization of AIC, the resources that constitute AIC form its foundation. However, which factors promote the accumulation of these resources in organizations and thereby enhance the organizational AIC have not been well studied. Based on previous literature on antecedents for organizational AI adoption and BDAC, this study refines three factors that may have an impact on the development of organizational AIC for demonstration and empirical testing. From an organizational level, exploration/exploitation strategies and leaders' AI knowledge may help improve organizational AIC. From a contextual level, institutional pressures may stimulate organizations to develop their AIC. Below the concepts of these three antecedents and related literature will be reviewed.

2.4.1 Exploration and exploitation

Exploration is a learning process that aims to experiment with new options (March, 1991). Thus, search, variation, risk-taking, discovery, innovation, and R&D are all part of this expression of organizational learning (Sinkula, 1994; Slater and Narver, 1994). According to Sitkin et al. (1994), exploratory activities are related to overall quality learning. These include things like trying out new abilities and resources, defining client demands via experimentation rather than taking them for granted, and taking part in activities that might result in game-changing concepts. According to March (1991, p. 85), "the distance in time and space between the locus of learning and the locus for the realisation of returns is generally greater in the case of exploration than in the case of exploitation, as is the uncertainty". March (1991) also affirms that the organizational return from exploration can be uncertain, distant, and frequently negative. In summary, exploration may be successful, but since it takes time, it may not be very efficient.

Exploitation is primarily concerned with honing and expanding current skills and capacities, while exploration is focused with questioning established notions with creative and entrepreneurial thoughts (March, 1991). The main idea behind exploitation is that by allocating enough or the majority of an organization's resources to maintain the sustainability in the face of opponents, one may establish a comfortable position in the market. As a result, the focus is on the organization honing in on its current resources and skills. Stated differently, operational efficiency is the focus, which is attained by doing comparable tasks more effectively (Porter, 1996). Refinement, production, efficiency, selection, implementation, and execution are a few examples of the activities that fall under the category of exploitation (March, 1991). Control, effectiveness, and dependability—or adhering to specifications—are the main priorities (Deming, 1981). Exploitation usually yields positive, local, and predictable rewards.

The terms "tendencies" and "orientations" (March, 1991) used to describe exploration and exploitation in the literature relate to the organizational tendencies, behavioural processes, and attitudes that show up in investment choices (Chandy and Tellis, 1998, p. 477). This study emphasises the antecedent importance of exploration and exploitation as orientations that propel the use of AI (i.e., capabilities). "The knowledge, skills, and related routines that constitute a firm's ability to create and deliver superior value" is what Day (1994, p.38) defines as competences. The way a company manages AI along these particular dimensions is presented as a competence that enhances the company's success.

Both approaches may produce value from technology, according to March (1991): exploration is the process of discovering new options, while exploitation is the extension of existing competencies, technologies, and paradigms. Making a decision might be aided by variables such as the degree of ambiguity surrounding the outcomes, the duration of the development, and the uniqueness of the development in comparison to the existing procedure (Kuittinen et al., 2013). It is advised to find a balance between the two strategies since relying too much on single one of them might be harmful because it can result in a "competency trap" (Liu, 2006). Organizations that make an effort to balance both are said to be ambidextrous (Tushman and O'Reilly, 2002; O'Reilly and Tushman, 2004). Accordingly, firms must possess certain skill sets in order to thrive in both new product and mature markets, which follow the norms of innovation, agility, and adaptability, as well as efficiency (Tushman and O'Reilly, 2002). Value creation may be seen as an outcome of ambidexterity, even when opposing schools of thought advise emphasising either one or both, which has been shown to be the most effective strategy for new venture's survival (Hill and Birkinshaw, 2014).

2.4.2 Leaders' AI knowledge

Based on the previous research and literature, leaders in the context of intelligent transformation can be described as those who try innovative technical solutions and take associated risks (Singh and Hess, 2020; Tumbas et al., 2018) and who are able to implement new technologies as well as novel concepts and ideas in the organization (Pierce and Delbecq, 1977). Leaders need to effectively respond to the challenges posed by new technologies (Zhu et al., 2006). They must be able to exploit innovation through technology orientation (Horner-Long and Schoenberg, 2002) while ensuring that technical innovation is coordinated with existing business processes to maintain the organization's competitive advantage (Rogers, 1995). Previous research has proposed some related concepts, such as "e-leadership" (Avolio et al., 2000) and "digital leadership" (Kane et al., 2019), to describe leadership forms that adapt to the development of advanced IT. For example, researchers believe that e-leadership means that leaders can (1) use IT to achieve multiple goals under appropriate circumstances; (2) select IT that best suits the value of various resources; (3) use existing technology at the best time; and (4) use capable IT when it is advantageous for a variety of reasons (Van Wart et al., 2019).

Similarly, in the context of AI application, firms need leaders to have professional knowledge of AI or choose technical experts who have the ability to handle specific IT implementation as leaders, serving as CDO, CIO, and CTO (Zhan et al., 2020). Goodall and Pogrebna (2015) emphasize that the link between leaders' knowledge/expertise and the organization's core business activities can improve organizational performance. Leaders with technical backgrounds can strategize AI (Carter et al. 2011). They can not only serve as technical experts to assist in the assessment, training, and selection of employees participating in AI projects, but also collaborate with other IT experts to create a good data environment and internal algorithm standards for AI implementation (Goodall and Pogrebna, 2015). Meanwhile, as digital strategists (McCarthy et al., 2022), such leaders are able to evaluate the possibility and necessity of building an AI-friendly organizational environment, and explain the feasibility of AI implementation and the strategic significance of developing AI to other top management members. In addition, leaders with AI knowledge influence perceptions of whether and when to make personnel adjustments to ensure that the organization owns and maintains a team that can work with AI (Ransbotham et al., 2019). These are all aspects that are beneficial to the development of AIC. Therefore, it can be considered that the leader's AI knowledge level can affect the improvement of firm AIC.

2.4.3 Institutional pressures

Institutional theory describes how external institutional pressures impact organizational behaviour and strategy, which in turn affects organizational decision-making (Kuo et al., 2022). Firms want to be accepted by society, yet they are constrained by external laws, customs, conventions, and values. According to Chu et al. (2018), conduct that complies with institutional and societal norms and expectations may be used to acquire, strengthen, or preserve legitimacy. Jiao et al. (2022) find managers often attempt to achieve societal approval while maintaining the necessary level of efficiency inside their organizations. Obtaining credibility may also provide access to valuable and rare resources, enhancing the organization's standing in the social network and, eventually, boosting its competitive edge (Yang and Su, 2014).

The theory states that coercive, normative, and mimetic pressures all have an impact on a firm's decision-making (Bag et al., 2021; Chatterjee et al., 2021; Chu et al., 2018). In order to handle the demands and preserve or increase their competitive edge, firms are compelled to use proactive methods. The conduct, structure, strategy, governance, and processes of organizations are all significantly impacted by these influences (Yang and Su, 2014). Jiao et al. (2022) list some possible sources of institutional pressures: regulators, key purchasers, media, peers or competitors, non-government organizations, environmental experts, industry associations, major business partners, fund providers, local communities, the public, special interest groups and other stakeholders.

It has been shown by prior research on institutional pressures that this theory may be used to investigate how AI techniques affect marketing and other domains. In order to preserve efficiency and satisfy stakeholders, organizations must carry out actions that are deemed lawful. As a result, they embrace cutting-edge technology like AI predictive analytics (Chen et al., 2021; Dubey et al., 2020). Additionally, as more managers have a combination of technical and managerial backgrounds, they may also feel more data-driven pressure (Dubey et al., 2020). The literature also shows that in a business environment, competitors that implement AI can exert pressure among related firms, stimulating others to increase their AI investments as this increases the overall competitive advantage (Bag et al., 2021). Furthermore, regulatory pressure from statutory bodies and pressure from customers and suppliers make organizations more likely to invest in the required AI infrastructure and technology (Bag et al., 2021). Firms also face external pressure, such as from governments, customers and competitors, to improve the skills of their employees to remain competitive. Bag et al. (2021) emphasize that the improvement of employee skills is positively related to the use of AI in the organization. Chatterjee et al. (2021) make the similar demonstration, while they focus on the adoption of AI-enabled customer relationship management in B2B environments. Jiwat and Zhang (2022) also propose the organizational requirements that may be needed to deploy AI resources in organizations. Due to improvements in operational efficiency, organizations looking to increase productivity, reduce costs, stay competitive, improve customer satisfaction and retention rates need to innovate their products or services and perform digital transformation of their businesses (Chatterjee et al., 2021). In terms of organization’s specific needs, a firm's internal needs, such as the need to identify and cultivate potential customers, discover new models and market segments, and contact relevant customer groups, are the antecedents for improving AIC (Borges et al., 2021). Finally, there are two external driving needs for organizations to implement AI. The first is data-driven competition among competitors, and the second is the rapid maturity of AI technique and the acquisition of big data (Jiwat and Zhang, 2022). These demands combined with other external institutional pressures enable organizations to strive to accumulate more AI-related resources and improve AIC in business activities.

2.5 Chapter summary

This chapter reviews and clarifies several basic concepts involved in this research, including AI, AIC, exploitation, exploration, data-driven culture, and institutional pressures. The definitions of AI and AIC are relatively complex, and the academics have not yet reached a unified consensus on these. This study selected their widely recognized and adopted definitions as the conceptual basis. Based on an interdisciplinary literature review of AI, this paper comprehensively reviews technical and nontechnical research on AI in business and management fields. It is found that there are big differences between nontechnical research on AI (focusing on the management theory and practice of AI applications) and technical research (focusing on AI technique research and development) in many aspects such as research focus, research methods, research theories, and understanding of AI. Therefore, continued and in-depth research on AI in the management field is very important. Meanwhile, it is important to pay attention to the distinction and combination of technical and nontechnical aspects in AI research. AIC is a new concept developed based on AI and RBV to measure the level of tangible, intangible, and human resources of an organization's use of AI technique. Given that there have been a large number of studies on organizational AI adoption intention, AIC is very important for studying organizations' use of AI and its impact. Furthermore, few studies have explored the antecedents that influence organizational AIC. Through literature review, exploration/exploitation strategies, leaders' AI knowledge, and institutional pressures are considered as the potential antecedents.

Chapter 3: Conceptual Framework and Hypotheses Development

3.1 Introduction

This chapter will first introduce the two main theories involved in this research, namely RBV and institutional theory. These are also the theoretical foundations for the hypotheses and models proposed by this study. According to the results of literature review, AIC will be further discussed and deconstructed into Nontechnical AIC (NAIC) and Technical AIC (TAIC), and the significance of this classification method will be explained. The second chapter has also reviewed the previous research on relevant topics, the antecedents for AIC, and its impact on company performance. On this basis, this chapter will further put forward the specific hypotheses of these influence relationships and add the relevant moderating variables. Finally, the specific conceptual model of the study is obtained for empirical examination.

3.2 Theoretical foundations

3.2.1 Resource-based view

According to the resource-based view (RBV), skills and resources differ between organizations, which in turn affects how well those firms operate and their competitive edge (Barney, 1991). RBV is one of the theoretical stances in strategic management that is most often used (Newbert, 2007). Resources and capabilities make up RBV's main constituents. While resources are defined as tangible and intangible assets (such as technological, human, and organizational resources), capabilities are the physical or intangible processes that enable the deployment of other resources and improve overall productivity (Akter et al., 2016). Organizations must generate and acquire resources that are valuable, rare, imperfectly imitable, and non-substitutable (VRIN) if they are to gain a competitive advantage (Barney, 1991). The relationship between a firm's resources, capabilities, and performance is often demonstrated using RBV (Barney, 1991; Chen and Lin, 2021; Hossain et al., 2021; Rahman et al., 2021).

In the IS literature, RBV has been frequently used to describe how organizations might achieve better performance and a competitive advantage. According to the notion, firm-specific, uncommon, and difficult-to-imitate resources and abilities can explain higher organizational performance (Barney, 1996; Bharadwaj, 2000). Organizational talents that are rare, nonreplaceable, and immune to imitation may provide a firm with more competitive edge (Barney, 1991; Amit and Schoemaker, 1993). Furthermore, the theory postulates that an organization's talents, competencies, and other resources vary among organizations and that these resources are what primarily determine an organization's performance. Companies will thus be able to maintain a sustained competitive advantage if they are able to recognise the qualities of resources or talents that competitors cannot imitate (Barney, 1991; Daft, 2015). Academics have recognised the significance of IT capability as a crucial organizational capability. In line with the RBV perspective, they have discovered that an IT capability that possesses the attributes of uniqueness, non-replicability, and non-substitutability can promote exceptional organizational performance (Wade and Hulland, 2004; Chen et al, 2014). However, research into the relationship between IT capability and better performance reveals that the way in which IT capability maximises the value of other organizational resources and capabilities may account for variation in performance outcomes (Ravichandran et al, 2005; Radhakrishnan et al, 2008). For example, although IT talents are important resources, they may also indirectly benefit the company by influencing other resources or capabilities (Kohli and Grover, 2008).

RBV has been the fundamental viewpoint for comprehending how IT investments create value and help firms achieve performance advantages (Wade and Hulland, 2004). When it comes to AI, it is crucial to know which resources to create in order to help firms get a return on their investment (Duan et al., 2019). RBV is quite pertinent to this research in this sense. Applications of the RBV across a variety of fields, such as marketing (Srivastava et al., 2001), supply chain management (Barney, 2012), and operations management (Bromiley and Rau, 2016), demonstrate the RBV's usefulness in understanding phenomena at the organizational level. RBV is now a widely accepted paradigm for creating theoretical justifications and conducting empirical tests to determine how organizational resources affect performance, with more than thirty years of empirical study (Barney et al., 2011). RBV is thus an appropriate theoretical framework for this study since resource-based AIC is its central focus, and part of its goal is to determine the conditions under which firms may build up AI resources, enhance their AIC, and acquire a competitive edge. Therefore, this study adopts RBV to help explain AIC.

3.2.2 Institutional theory

The adoption of certain practices and activities by an organization may be influenced by external pressures, as explained by institutional theory (DiMaggio and Powell, 1983; Hirsch, 1975; Meyer and Rowan, 1977). According to this theory, a company functions within a social framework consisting of values, customs, norms, and presumptions that establish what is appropriate for the firm (Peng et al., 2009). According to this idea, the external environment of an organization is referred to as the institutional environment, and it has a significant impact on how the organization behaves (Tina Dacin et al., 2002).

In terms of an organization's ability to adopt innovation, institutional theory also emphasises the impact of external environmental factors. It contends that institutional decision-making is influenced by social factors such as political and social pressures in addition to organizational goals (Oliver, 1997). These forces encourage firms in the same sector to become homogenous by copying the actions of industry leaders. This hypothesis has been used in earlier research to explain the IT adoption (Purvis et al., 2001; Chatterjee et al., 2002; Teo et al., 2003). Bag et al.'s recent study (2021) also looks at how stakeholder pressure may affect an organization's choice to adopt AI and how that decision may affect firm performance. It is often acknowledged that trade partner pressure also plays a significant role in IT adoption (Lin H. and Lin S., 2008; Premkumar and Ramamurthy, 1995). In order to stay in step with its business counterparts and preserve internal harmony, an organization can follow to use new technologies. Although institutional frameworks in many countries are not always well-arranged, governments also have a significant impact on firms (King et al., 1994; Montealegre, 1999). The government would help firms with policies that encourage them to adopt AI if it is resolutely dedicated to AI approaches. In a well-regulated environment, the government provides the necessary infrastructure, a favourable legislative framework, and regulatory guidelines to incentivize firms to implement AI. This favourable association between firms' desire to embrace IT and the regulatory environment has been proven by a few empirical research (Kuan and Chau, 2001; Wang and Cheung, 2004).

Three distinct forms of institutional isomorphism have been recognised by DiMaggio and Powell (1983): coercive, normative, and mimetic. Industry and other professional groups, government regulations and directives, or minimum competition requirements within an industry or market sector are all sources of coercive pressure (Demirbag et al., 2007). It also results from coercive demands from other organizations that force the adoption of new practices (Kauppi, 2013). In addition to financial incentives, normative pressures may also have an impact on technology adoption (Dubey et al., 2019a). The professionalisation of the company—which is brought about by a workforce that is well-educated, well-versed in technology, and open to embracing it—causes normative pressure (Dubey et al., 2019a). Firms will use novel technologies to keep up positive ties with others and preserve the cooperative spirit. Normative pressure is therefore in charge of the choice and implementation of new technology (DiMaggio and Powell, 1983). Mimetic pressure, which may result from a lack of direction and technology expertise, refers to an organization's propensity to imitate others. According to Srinivasan and Swink (2018), organizations tend to emulate other successful competitors. Firms are aware of external pressures in these three aspects and realize the need to increase its AIC to gain a sustainable competitive advantage. Therefore, institutional theory could provide solid theoretical support for this study.

3.3 Nontechnical and technical AIC

To interpret how firms utilize AI-related resources for competitive advantages and the specific impact of AI on organizational performance, AIC's idea and framework were suggested by researchers who also established its scale and investigated the effects of AIC on organizational performance and creativity (Mikalef and Gupta, 2021). Academics introduced the idea by citing AI research in the context of business and RBV that explains sustained competitive advantage, as well as IT capabilities (Shan et al., 2019). The ability of an organization to use AI resources to assist operations is central to the concept of AIC. A rising corpus of research is exploring how AI technologies and approaches might be used to achieve organizational objectives, since the technology is becoming an increasingly valuable asset for organizations (Schmidt et al., 2020; Wang et al., 2019). In order to clarify how this value is obtained and how firms can set up to maximise the return on their investments in AI, AIC has been established. Based on this, Mikalef and Gupta (2021) have also created a scale to assess how AIC and organizational creativity and performance relate to each other in organizations, suggesting that AIC may enhance these attributes.

This perspective on AI from organizational capability is widely used in research, and the field keeps expanding on this idea. Although there are some minor differences in the definitions, they all cover what an organization should be able to do with investments in AI, and some additionally provide the intended results of implementing AI. For example, AIC is defined as "the ability of organizations to use data, methods, processes, and people in a way that creates new possibilities for automation, decision making, collaboration, etc. that would not be possible by conventional means" by Schmidt et al. (2020). This definition falls into the latter category. In addition to information and techniques, this definition also covers the people and procedures needed to coordinate and use AI. In a similar vein, other definitions include the supplementary resources needed to profit from AI methods (Wamba-Taguimdje et al., 2020). The common thread throughout these definitions is the recognition that AIC pertains to an organization's utilisation of AI-specific resources to facilitate value generation (Schmidt et al., 2020; Wamba-Taguimdje et al., 2020). These AI-specific resources might be nontechnical, like staff skills and attitudes (Wamba-Taguimdje et al., 2020), or technical, such training data and AI algorithms (Schmidt et al., 2020). As a result, the idea of AIC broadens the perspective on AI by focusing not only on technical resources but also on all relevant organizational nontechnical resources that are crucial for realising AI's full strategic potential (e.g., a firm's ability to choose, manage, and employ its resources tailored to AI). In addition, AI itself is a multidisciplinary concept (Dwivedi et al., 2021). It requires contributions from many nontechnical disciplines including philosophy, psychology, law, and linguistics. Existing literature also supports the distinction between viewing AI resources from both technical and nontechnical perspectives (Chowdhury et al., 2023; Samoili et al., 2020). Meanwhile, through the review of AI research in management, it is found that scholars have a large cognitive difference between the technical and nontechnical aspects of AI (Cui et al., 2022).

From the theoretical perspective of RBV, nontechnical and technical AI resources correspond to different characteristics of the VRIN framework. Specifically, technical AI resources are more in line with the features of being valuable and rare. First, high-quality data and advanced data processing techniques can provide valuable insights for firms and improve the effectiveness of decision-making (Ghasemaghaei and Calic, 2019; Szukits and Móricz, 2023). Powerful AI algorithms and models can also solve complex systemic problems, which highlights the value of technology (Rivard et al., 2006). Secondly, the most advanced algorithms, models, or AI tools are often scarce in the market, and are even exclusively owned by some particular firms (Ragavan, 2017; Safadi and Watson, 2023). Especially when those themselves own patents and intellectual property rights related to these AI techniques, it will be more difficult for competitors to obtain the same technical resources (Rikap, 2022). However, the disadvantage of technical resources is that they can be imitated and replaced

(Clemons and Row, 1991). For example, firms can obtain the same data sources, develop similar AI techniques, and even poach the technical talents and knowledge of competitors at high prices (Dauvergne, 2020). Moreover, existing AI tools will always be replaced by more advanced techniques in the future (Lu, 2019; Shao et al., 2022).

On the other hand, firms' nontechnical resources such as the organizational structure, culture, governance methods and business processes often have their own characteristics, which can create unique competitive advantages that are difficult to imitate and substitute (Barney, 1986; Hitt et al., 1998; Zheng et al., 2010). For example, a firm may have unique decision-making processes and management practices that have been optimized and adjusted over a long period of time and are difficult to be imitated by other competitors (Kunc and Morecroft, 2010; Liu and Liang, 2014). The unique communication mechanism and cooperation mode within the firm enable itself to efficiently execute AI projects. Excellent leaders also have unique management and leadership styles, which are often a combination of personal abilities and experience (Wallis et al., 2011). In short, organizational culture is the result of a variety of factors, including history, values, employee behaviour, and leadership style, and this complexity makes it difficult for competitors to replicate (Carmeli, 2004). In addition, firms often have distinct strategic execution, internal training systems, and customer relationships (Olson et al., 2005; Schwartz and Davis, 1981). In particular, they may have training programs customized for their own business and technical needs, which can continuously improve employees' AI-related skills and innovation capabilities (Jehanzeb and Bashir, 2013; Jaiswal et al., 2022), and external substitutes are difficult to provide the same effect (Collis and Montgomery, 2008; Blanchard and Thacker, 2023). Long-established customer relationships and trust are also unique resources, which means competitors could not obtain the same customer loyalty through simple alternative means (Wang and Feng, 2012). However, not all nontechnical resources directly create value (Grönroos, 2008). For example, some traditional managerial and cultural practices may not contribute significantly to the current AI strategy of the firm, and may even hinder its innovation and change (Goncalves et al., 2020). Whether nontechnical resources are rare also depends on their prevalence and availability to competitors (Newbert, 2008; Klein, 2011). Today, most companies have their own unique culture and governance structure (Saarikko et al., 2020). In other words, organizational culture as a resource is relatively not that rare because it is a common practice among firms.

Therefore, it is necessary to analyse AIC and its role from the perspectives of technical and nontechnical resources. Firms need to accumulate corresponding resources to develop both their nontechnical AIC (NAIC) and technical AIC (TAIC). According to the findings from research review (chapter 2.3), this study defines NAIC and TAIC mainly based on their differences in the focus on AI techniques. Referring to Mikalef and Gupta (2021), **NAIC means the ability of firms to build, integrate, and utilize AI-related resources that do not directly impact firms' AI technical advancement**. NAIC includes the aspects of business skills, inter-departmental coordination, organizational change capacity, and risk proclivity, which are the critical resources for business performance improvement (Belhadi et al., 2021; Lou and Wu, 2021; Mikalef and Gupta, 2021). Making effective use of AI propensity is also important (Ashaari et al., 2021). Even having access to very powerful AI resources will not assist if firms are unwilling to use AI for planning, coordination, or control (Denicolai et al., 2021). On the other hand, major infrastructural resources are needed for the successful and efficient implementation of AI in business (Bag et al., 2021; Chatterjee et al., 2021). These resources include financial support (Łapińska et al., 2021), data (Herhausen et al., 2020; Hwang and Kim, 2021), hardware and software (Zhang et al., 2020), and technical skills (Rahman et al., 2021). **The ability to make use of these resources, different from NAIC, could directly lead to the improvement of AI techniques in firms, which is defined as TAIC.** So the basic resources, data, technology, and technical skills constitute a firm's TAIC. Employee technical proficiency and knowledge in particular would make it easier for AI-related technologies to proliferate (Chatterjee et al., 2021). For firms to use AI in the near future, they must first comprehend the range of applications available and have the necessary skills and knowledge to operate AI systems (Vrontis et al., 2022).

3.4 Research hypotheses

3.4.1 Firm-level antecedents

Exploration, exploitation and AIC

For organizational R&D, figuring out the difference between exploration and exploitation is a significant difficulty. Activities intended to produce new knowledge are referred to as exploration, and they involve searching, experimenting, and methodical attempts to create innovations that are more uncertain and go beyond the current skill set of an organization. The process of refining current assets and carrying out actions intended to generate value from proven capabilities is known as exploitation (March, 1991). When it comes to innovation, the exploration-exploitation typology is often defined as the distinction between the creation of a new technology and the improvement of an already existing one (Winter, 1971). It has been observed, therefore, that in order for firms to fully use AI, they must create and modify their value-creating procedures, business plans, and entrepreneurial endeavours (Burstrom et al., 2021; Chalmers et al., 2021). AI-related R&D efforts play a significant role in setting up or organising firm capabilities and operations in order to generate value.

Brock and von Wangenheim (2019, p. 125) have suggested firms should adopt a "dual-sourcing strategy" to acquire technical AI skills, which means "exploiting internal skills and sourcing external talents" simultaneously. In essence, exploitation is the use of knowledge, which is operationalized in identifying and grabbing new business possibilities (Teece, 1998). While exploration is a time-consuming and inherently risky activity, exploitation approach operates more like a rapid and predictable adaption (Real et al., 2006). Therefore, firms that need to quickly and cheaply apply AI approaches may find exploitation to be more appropriate. Put another way, exploitation may assist firms in acquiring current AI methods and expertise as well as replicable AI resources fast. Furthermore, the strategy of exploitation operates via the acquisition of knowledge and signifies the firm's capacity to identify and assimilate relevant information (Liao et al., 2009), which is often related to both technical and nontechnical organizational skills or experience. On the other hand, for a firm to prepare technologies for digital transformation, exploration is also an effective approach to technological entrepreneurship (Jafari-Sadeghi et al., 2021). The unique or innovative AI techniques that organizations possess are difficult to replicate or acquire, and primarily need to be explored by the firms themselves. This could take a long way to go with a large amount of time and funding resources invested (Fountaine et al., 2019). A unique capability might result, for instance, from the creation of a proprietary algorithm that predicts outcomes more accurately or that operates quicker or more computationally efficiently than earlier algorithms (Real et al., 2006). According to Crossan and Berdrow (2003), these unique techniques assist the company in developing a distinct value offer for the clients, giving it a competitive edge. In some situations, exploration may also assist firms in gaining fresh insights that are not directly related to AI methods. For example, researching consumer needs and the competition in the market is a part of exploration when developing new products (Rothaermel and Deeds, 2004).

For NAIC, first, by exploring cutting-edge AI applications and trends, firms can develop unique AI strategies and visions (Gill et al., 2022; Allioui and Mourdi, 2023). Such strategies and visions are often based on the firm's own history, culture, and market insights, and are difficult to be imitated by competitors (Furr and Eisenhardt, 2021). Secondly, by exploring new management and decision-making processes, a unique innovation culture and management advantages can be created, especially to ensure the efficient execution of AI projects and resource optimization (Chatterjee et al., 2021). In addition, by exploring new talent recruitment, training and development plans, firms can form its own talent management system (Jafari-Sadeghi et al., 2021). These exploration strategies are based on the specific needs and development paths of the firm and are difficult to imitate or replace (d'Armagnac et al., 2022). Google has worked with well-known leadership training institutions to design a series of customized training courses. At the same time, it explores project cooperation and team building activities among multiple departments to strengthen employees' teamwork and problem-solving abilities (Tran, 2017). Amazon is also committed to improving employees' innovation capacities and exploring relevant training projects to promote its continuous innovation and market competitiveness (Rikap, 2023). It is worth noting that these programs are designed and implemented by the firm based on its own culture, strategy and market needs, which are difficult for other competitors to imitate, and there are few similar alternatives that can substitute them. Therefore, it can be assumed that:

H1a. Firm's exploration is positively related to its NAIC.

For TAIC, in terms of data, by exploring new methods of data collection and processing, firms can improve the quality and utilization efficiency of data, thereby improving the performance of AI tools (Aldoseri et al., 2023). In terms of technology, exploring new AI algorithms and techniques can directly enhance firm's competitiveness (Jafari-Sadeghi et al., 2021). For example, developing better ML algorithms can significantly improve the accuracy of prediction models, thereby providing firms with greater business value and competitive advantages (Lee and Shin, 2020; Borges et al., 2021). In terms of infrastructure, exploring new and scarce computing architectures and hardware resources, such as quantum computing and edge computing, can significantly improve the processing power and efficiency of AI models (Dunjko and Briegel, 2018; Cao et al., 2021). Typical cases include Google's exploration of the leading TensorFlow framework and a variety of advanced AI models, which are notably superior to other techniques on the market in terms of performance and application scope, forming its own rare AI technical advantage (Abadi et al., 2016). Another example is Amazon's exploration of a precise personalized recommendation system. This significantly improves customer experience and sales conversion rate, creating huge business value for Amazon (Smith and Linden, 2017). In light of this, it can be surmised that:

H2a. Firm’s exploration is positively related to its TAIC.

By exploitation strategies, firms can also optimize existing culture and organizational structure, thus improving decision-making mechanisms (Hahn et al., 2015; Shrestha et al., 2019). Through employee training, firms can improve employees' existing skills (Greco et al., 2019; Katou, 2022). These are all related to enhancing firm NAIC (Mikalef and Gupta, 2021). For example, Netflix encourages employees to further apply AI technology based on its open and innovative internal culture, which cultivates employees' innovation and problem-solving capabilities (Lee et al., 2020). Starbucks has carried forward its existing customer service standards and coffee culture, improving customer loyalty and brand value (Son et al., 2019). In fact, other firms cannot easily imitate and obtain these nonsubstitutable resources related to NAIC. It can be inferred that:

H1b. Firm’s exploitation is positively related to its NAIC.

Exploitation may also have positive effects on TAIC (Brock and von Wangenheim, 2019). Walmart integrates its global big data accumulation and AI algorithmic R&D achievements into the Eden platform (Mohan, 2021). Through this integration, Walmart is able to monitor and analyse a large amount of sales data and inventory information in real time, optimizing supply chain management and commodity distribution strategies (Cao, 2021). The application of the Eden platform enables Walmart to more accurately predict consumer demand and adjust inventory and supply chain strategies in a timely manner to respond to market changes and save costs (Weber and Schütte, 2019). This market application not only improves efficiency, but also enhances Walmart's competitive advantage in the retail industry (Kabir et al., 2023). Therefore, through integration and optimization of existing resources, firms can improve the efficiency and effectiveness of AI techniques, thereby directly creating value and maintaining the rarity of technical resources. As a result, it can be assumed that:

H2b. Firm's exploitation is positively related to its TAIC.

Leaders' AI knowledge and AIC

In the context of implementing AI in organizations, the relevant leaders are generally defined as those who have the ability to understand and apply AI techniques and can guide organizations to succeed in digital transformation and technological innovation (Westerman et al., 2014a). These leaders not only need traditional management and leadership skills, but also need to have a deep understanding of AI techniques and be able to apply these techniques to firm strategy and operations (Davenport, 2018; Marr, 2019). In this research, leaders mainly refer to the CDO, CIO, or CTO of the firm, as well as other top management members who understand the firm strategies related to AI applications.

Studies reveal that when an organization tries to introduce a new technology or system in the hopes of obtaining a greater competitive edge, its employees are seen to display both explicit and implicit actions in opposition to the change (Kim and Kankanhalli, 2009; Rialti et al., 2019). Nonetheless, leadership may play a part in resolving this issue (Zhang et al., 2020). According to other research, a supportive leadership style may be a positive element in lowering employee resistance and ensuring the smooth deployment of new systems inside the organization (Shao et al., 2016). Senior executives are responsible for leading firm operations and developing the AI strategy. As the top decision-maker, leaders can best understand the organizational resources and capabilities most relevant to AI. The upper echelon theory holds that organizational outcomes and strategic choices come from choices made by upper echelons that reflect their values, cognitions, and perceptions (Carpenter et al. 2004; Hambrick and Mason, 1984). This cognition can be measured through observable individual and group characteristics, such as career experience, educational background, socioeconomic background, financial status, etc. (Klein and Harrison, 2007). Leaders with less technical expertise may find it difficult to understand the logic and process by which AI makes decisions, leading to confusion, uncertainty, and worry about AI (Brock and von Wangenheim, 2019), and even reputational and financial risks for the firm (Oliveira et al., 2022). Conversely, leaders with more technical expertise and experience may have greater ability to shape AI strategies to achieve desired outcomes (Singh and Hess, 2020). Additionally, leaders with high levels of AI knowledge may better understand the benefits of supporting AI applications and evaluate AI-related strategic issues (Pan et al., 2019). Thus, leaders' AI knowledge may play a role as the firm-level antecedents for AIC. It can be assumed that:

H1c. Leaders' AI knowledge level has a positive relationship with NAIC.

H2c. Leaders' AI knowledge level has a positive relationship with TAIC.

3.4.2 Context-level antecedents for AIC

Institutional pressures and AIC

Organizations must take the required steps to remain competitive after carefully weighing the institutional pressures. Coercive, normative, and mimetic pressures are the three primary categories of institutional pressures. In the process of firms applying AI techniques, coercive pressure refers to the legal, regulatory and policy requirements from governments, regulators, or industry standard constitutors. This kind of pressure requires firms to follow relevant legal, ethical and privacy protection regulations when using AI to ensure that their behaviour is legal and compliant (Bag et al., 2021; Chu et al., 2018). Government agencies' regulatory policies, also referred to as regulatory pressure, are a kind of coercive pressure that may affect a firm's decisions. Regulatory pressures are often used in conjunction with fines, oversight, or rewards to govern industry performance as a whole (Chu et al., 2018). The pressures function as planned, with firms feeling under pressure to act in a certain manner and adhere to rules in order to establish credibility and avoid needless fines. Governments, laws and rules, industry groups, and standards that safeguard data for secure use are also potential sources of coercive pressure when investing in enhancing AIC (Bag et al., 2021). Furthermore, a company's AI-related operations are probably going to be impacted by the constantly shifting needs of its users and customers, as well as their growing privacy concerns. Finally, stakeholders like investors and board members could also want firms to use the data at their disposal to enhance strategic decision-making and efficiency—as long as they do so within the bounds of privacy regulations.

The aforementioned coercive forces may prompt corporations to adopt a more proactive approach towards using AI to address various demands, including the management and utilisation of ever-growing consumer data. An organization's ability to learn from and take use of the innovations and knowledge is made available by AI (Mikalef and Gupta, 2021). Positive attitudes towards AI, drawing similarities to IT proactivity, may encourage firms to experiment more with AI infrastructure, tools, and strategies for integrating data management services, architectures, and security. As a result, new AI breakthroughs may be produced that improve methods of carrying out market research, raising consumer happiness, or successfully adapting to the changing market needs (Nwankpa and Roumani, 2016). According to Wang et al. (2012), managers may face pressure from other stakeholders, including investors and board members, to use AI resources to support business objectives. This will require them to undertake an effective AI planning process and create and integrate a strong AI strategy with strategic business planning. Therefore, following hypotheses are formulated:

H1d. There is a positive relationship between coercive pressures and firm’s NAIC.

H2d. There is a positive relationship between coercive pressures and firm’s TAIC.

Based on expectations, shared obligations, and standards created to execute the proper actions, normative pressures ensure that firms carry out organizational activities that are seen as legitimate (Greenwood et al., 2002). Normative pressures drive firms to adopt AI techniques and applications that comply with industry best practices and professional standards to improve overall technical reliability (Jiao et al., 2022; Kuo et al., 2022). Suppliers, vendors, consumers, trade unions, and other industry groups are potential sources of the values and behaviour standards (Chu et al., 2018; Bai et al., 2021). The firm's need for recognition and to become more legitimate and visible is accompanied with normative pressures (Lin et al., 2021). It is often considered innovative to invest in disruptive and developing technological initiatives, such as AI in marketing. Furthermore, companies may behave in accordance with expectations of becoming, for example, a data-driven organization that uses AI for a variety of functions, given that both digital and AI transformation are hot topics in most sectors. Managers will naturally feel pressured by this to include AI planning into their entire company strategy. By doing so, they might establish a reputation for innovation and increase firm exposure, credibility, and access to important resources like business experts who add to the total worth of the company (Bai et al., 2021; Lin et al., 2021). Therefore,

H1e. There is a positive relationship between normative pressures and firm’s NAIC.

H2e. There is a positive relationship between normative pressures and firm’s TAIC.

When firms mimic the organizational actions of their competitors, often with an attempt to achieve comparable outcomes, they are frequently subject to mimetic pressures. Considering technical uncertainty and market competition pressure, firms can reduce risks for implementation and enhance competitive advantages by imitating or copying the AI application cases and practices of other successful ones (Marr, 2019). This pressure comes from benchmark competitors and successful cases in the industry (Jiao et al., 2022; Dahlke et al., 2024). When faced with fresh demands, managers often lack confidence in their ability to take credible action, which makes them justify copying the successful cases. The effective use of AI by competitors in their organizational operations may put pressure on the whole industry to engage in AI adoption. These formidable firms force the others to emulate their actions and conform to the best practices and standards in the sector (Jiao et al., 2022). According to Bai et al. (2021), mimetic pressures have great potential to be agents of change as well as educational opportunities. Companies could attempt to copy not only the technology but also the workspaces of their prosperous rivals. This might result in more money being spent on AI experiments, which would then gradually boost the use of AI. It also helps to foster a positive work environment for staff. In summary, following opponents may lead to more IT proactivity, infrastructure investment in AI, and pressure on firms to create clearer visions for AI contributions, and more effective planning for AI implementation. Therefore, following hypothesis is formulated:

H1f. There is a positive relationship between mimetic pressures and firm’s NAIC.

H2f. There is a positive relationship between mimetic pressures and firm’s TAIC.

3.4.3 AIC and firm performance

According to Dubey et al. (2020), firm performance (FP) is a crucial metric for evaluating a company's operational, marketing, financial, and innovative performances. Business performance and a company's health may both benefit from AI (Yasmin et al., 2020). AIC improves the quality and efficiency of decision-making by enabling firms to methodically gather, assess, and analyse the information suggested by AI systems (Ashaari et al., 2021). AI can provide practical answers to challenging issues (Awan et al., 2021), offering a more trustworthy foundation for decision-making (Elia et al., 2021). AI systems provide administrators and company leaders knowledge that has been generated from data so they may address current and future issues (Ashaari et al., 2021). As evidenced by studies on business innovation (Chaudhuri et al., 2021), supply chain resilience (Zhang, Z. et al., 2021), efficiency gains, cost savings, product quality improvements, and customer service improvements (Bag et al., 2021), executives are gradually paying more attention to TAIC. Organizations may greatly increase their operational performance and efficiency by using AI-assisted decision-making (Ashaari et al., 2021). Therefore, firms may get greater performance and productivity by using and optimising their TAIC (Chatterjee et al., 2021).

Research has extensively demonstrated the relationship between IT competence and organizational success (Bharadwaj, 2000; Hitt and Brynjolfsson, 1996). Based on empirical data, organizations may enhance their performance by using advanced IT capabilities (Melville et al., 2007; Stoel and Muhanna, 2009; Chen et al., 2014). Nonetheless, several studies continue to question whether IT capabilities directly affects how well an organization performs (Carr, 2003; Chen et al, 2014). Consequently, opinions regarding how IT capability (e.g., NAIC) supports organizational performance are divided in the literature (Melville et al., 2007; Kohli and Grover, 2008). Some studies even contend that the relationship between IT capability and organizational performance needs to be re-examined (Chen et al., 2014). However, IT expertise still has a big impact on how well firms operate. In fact, in an increasingly competitive business environment, firms may distinguish their product offerings and carve out market niches because of IT capabilities like NAIC (Tan and Teo, 2000). Similarly, Bharadwaj (2000) discovered that companies with more IT capabilities often outperform their competitors when analysing organizational performance using a profit and cost-based performance matrix. In order to perform better, firms with higher NAIC scores are thus better equipped to mobilise, deploy, and combine AI resources with other available resources.

Specifically, first, excellent business skills mean that the firm leaders can make use of AI-related resources, coordinate AI-related activities, and demonstrate strong leadership to assist AI projects (Davenport and Ronanki, 2018; Fountaine et al., 2019; Wamba-Taguimdje et al., 2020). Furthermore, firms can understand and respond to market needs faster than competitors and provide more attractive products and services (Hitt et al., 1998). Meanwhile, accurate market positioning and effective customer service help firms improve customer satisfaction and market share, thereby increasing profitability (Anderson et al., 1994). Secondly, good organizational change capacity enables firms to continuously adjust and optimize themselves to adapt to market and technical changes, which is an important strategic resource (Mikalef and Gupta, 2021; Widianto et al., 2021). The lasting organizational change and optimization help firms promote innovation and maintain the long-term competitiveness (Tushman and O'Reily, 2002). Third, inter-departmental collaboration can facilitate the sharing of resources and knowledge, reduce information islands and resource waste, and improve decision-making and execution efficiency (Cuijpers et al., 2011). The combination of knowledge and skills from different departments can also generate more innovative ideas and solutions and enhance firm's innovation performance (Darroch, 2005). Finally, a moderate risk proclivity helps firms maintain a proactive attitude in technical innovation and market changes (García-Granero et al., 2015; Roper and Tapinos, 2016). Firms can more actively apply AI techniques, seize growth opportunities, and realize business expansion (Brynjolfsson and McAfee, 2017). Given these points, the following assumption can be made:

H3a. Firm's NAIC has a positive effect on its performance.

Although "the value of competitive advantage does not lie in the capabilities themselves, but in the way the resources and capabilities are exploited", the functionality of dynamic capabilities is likely to be common (e.g., similar business capabilities powered by AI that can be acquired in the open market) (Eisenhardt and Martin, 2000, p.1117). The ability to use dynamic capabilities sooner, more cleverly, or more coincidentally than the competitors to generate resource configurations that have the advantage, therefore, represents the possibility for long-term competitive advantage. The influence of business analytics adoption on company performance remains unclear, even with the growing popularity of new technologies such as business intelligence and big data analytics (Akter et al., 2016; Wamba et al., 2017; Ramanathan et al., 2017; Aydiner et al., 2019; Dubey et al., 2019b). Through business processes, Aydiner et al. (2019) investigated how business analytics affected operational performance. In a similar vein, one may argue that strengthening TAIC aids in an organization's information processing capacity development (Srinivasan and Swink, 2018). They may use it to understand and synthesise complicated data from several sources, which managers can use to lower uncertainty about supply availability, capacity, and demand (Chen et al., 2015; Dubey et al., 2019b). Without these skills, firms must keep a lot of goods on hand or make investments in response to flexible supply chain architecture, which has an impact on their profit margins. Furthermore, it is proposed that the insights obtained by TAIC provide organizations with chances to reorganise their resources in a manner that enhances their ability to adjust to changing circumstances and improves their alignment with partners (Duan et al., 2019). When taken as a whole, these effects of TAIC usage may show up as improved firm performance (FP).

Taking into account the specific aspects of TAIC, first of all, efficient data management and in-depth data analysis capabilities enable firms to extract valuable information from large amounts of data and make more reasonable strategic decisions (Shamim et al., 2019). Secondly, the ability to develop and optimize AI algorithms is an important technical resource (Chowdhury et al., 2023). Through more advanced AI techniques, firms can not only automate and optimize many business processes, reduce operating costs, and improve production efficiency, but also develop new products and services (Mithas et al., 2022). This allows firms to significantly enhance their competitive advantage. Thirdly, powerful computing resources and secure network infrastructure are important supports to continue and efficiently develop and apply AI (Gill et al., 2022). In addition, talents with deep AI knowledge and skills are also rare resources and can contribute to a firm’s technical advancement and innovation performance (Dickson and Nusair, 2010). Alternatively, firms can organize learning and training programs to enable technical teams to continuously update their knowledge and maintain the leading position in the industry. Especially when technical talents have the ability to collaborate across different disciplines and solve complex problems, firms can thus efficiently respond to various technical challenges and business needs (Lee et al., 1995). So it can be assumed that:

H3b. Firm's TAIC has a positive effect on its performance.

3.4.4 The moderating role of data-driven culture

A third variable may have an impact on a variable connection between two constructs by altering the relationship's direction, speeding or delaying it, or both, which is called a moderator. One of the most significant challenges to be solved is transforming the current IT and business culture to maximise AI investments (Wamba-Taguimdje et al., 2020). In order to maximise the benefits of using AI, it is essential to thoroughly evaluate the influence of organizational culture. According to earlier research on technology adoption, organizational culture has a significant impact (Duan et al., 2019). In order to make correct decisions and enhance performance, AI interacts with an organization's culture (Chatterjee et al., 2024). AI is seen as a crucial tactic to get a competitive edge (Shi et al., 2020) and leverages massive data sets to assist complete activities and allow improved decision-making by delivering wider insights (Mazzone and Elgammal, 2019). However, there are great difficulties in adapting to the big data environment in terms of management and culture (Brynjolfsson and McAfee, 2011; Wang, Y. et al., 2016). To be successful in AI applications, big data awareness must be established throughout the firm and big data transformation implemented throughout the organization. In the literature, there are many studies that use culture as a moderating variable which helps firms achieve better innovation outcomes (Hynes, 2009; Prajogo and Ahmed, 2006). Accordingly, this study considers data-driven culture as a key factor in improving firm's AIC.

Without organizational and employee buy-in for data-based analytics and acceptance and readiness for AI initiatives, firms will face failure (McAfee and Brynjolfsson, 2012). Some researchers note that firms are not always successful in their AI investments, because some do not consider the cultural dimension (Beath et al., 2013; Lavelle et al., 2013). Cultural readiness for AI initiatives is arguably more important than the AI applications themselves. Data-driven culture is a culture in which decision makers base their decisions on insights extracted from data rather than intuition (Beath et al., 2013; McAfee and Brynjolfsson, 2012). It directly influences how data is collected, analysed, and used within an organization, which is associated with the deployment and effectiveness of AIC (Liu et al., 2022; Chatterjee et al., 2024). In contrast, other potential moderators, such as organizational structure or market conditions, might have a more indirect impact on AI utilization (Jöhnk et al., 2021). Data-driven culture also fosters an environment where decisions are made based on analytical insights derived from data (Szukits and Móricz, 2023). This is highly relevant for AIC, as the primary purpose of AIC is to provide advanced analytics and predictive capabilities as well as enhance the decision-making processes (Mikalef and Gupta, 2021). Moreover, AI optimization is based on a kind of data-driven iteration (Jin et al., 2018). From this perspective, data-driven culture promotes continuous learning and improvement by consistently using data to monitor performance and refine processes (Ghafoori et al., 2024). This is essential for AI systems, which require ongoing updates and improvements to remain effective (Dwivedi et al., 2021). The other benefits of forming a data-driven culture include reducing biases by using empirical evidence (Karaboga et al., 2023), scaling and adapting AI solutions across the organizations (Chaudhuri et al., 2021), and so on. Hence, it can be assumed that:

H4a: Data-driven culture moderates the relationship between firm's exploration and NAIC.

H4b: Data-driven culture moderates the relationship between firm's exploitation and NAIC.

H4c: Data-driven culture moderates the relationship between leaders' AI knowledge level and NAIC.

H4d: Data-driven culture moderates the relationship between firm's exploration and TAIC.

H4e: Data-driven culture moderates the relationship between firm's exploitation and TAIC.

H4f: Data-driven culture moderates the relationship between leaders' AI knowledge level and TAIC.

3.4.5 The moderating role of firm's international presence

Firm internationalization-related factors have not been well investigated in research as moderators of the effect of AI deployment on firm performance. The advantages of digital globalization—a greater degree of digital intensity in the asset bases of multinational firms and the related financial services systems—must be taken into account, according to Verbeke and Hutzschenreuter (2021). Building on this view, it is reasonable to concentrate on whether and how a firm's introduction into foreign markets moderates the link between its AIC and performance. Studies have looked at how internationalisation affects performance (Arte and Larimo, 2021; Denicolai et al., 2021) and how it acts as a moderator in different situations (Cho and Kim, 2017). Although AI resources have advantages, they are costly to get and need time to create and become proficient in. Consequently, firms may increase the benefits of high levels of AIC on performance via learning, scalability, and network effects brought about by improved global resource orchestration (Zeng et al., 2021). For instance, foreign markets provide more data, which AI techniques might use to assist firms in identifying more lucrative and devoted clients (Agarwal and Dhar, 2014). There are also connections between internationalization and digital innovation since multinational corporations have a wealth of resources and a well-established reputation for their global impact (Juergensen et al., 2021). Firms can also gain efficiency benefits through internationalization, because AI technique can help international firms optimize operations and thereby improve performance (Agarwal and Dhar, 2014). They may lower some of the expenses associated with managing technological complexity and enhance the coordination of AI approaches with the use of global organizational learning (Luo, 2022; Mees-Buss et al., 2019). According to Buckley and Strange (2015), executives in multinational companies possess a greater ability to use AI techniques to enhance their organizational structure and create more effective global value chain systems.

International business operations inherently introduce greater complexity due to factors like diverse regulatory environments, cultural differences, and varied market conditions (Sun et al., 2021). The ability of AI techniques to manage and optimize these complexities can have a pronounced impact on firm performance (Ahi et al., 2022; Ghauri et al., 2023). In terms of data, firms operating internationally gather data from a wide range of sources and markets and enhance the richness of their datasets (Akter et al., 2021). This variety can improve the robustness and accuracy of AI models, leading to better insights and decision-making (Aldoseri et al., 2023). During the process of internationalization, AI can also help firms tailor their products, services, and strategies to local markets, giving them a competitive edge (Allioui and Mourdi, 2023). This localization capability is crucial for international success and could directly improve firm performance (Law et al., 2009). Overall, firms could obtain insights through AI into global trends, foreign consumer behaviours, and international market dynamics, which is particularly valuable for its performance (Cao, 2021; Haleem et al., 2022). Because these insights can drive strategic decisions that enhance performance (Mikalef et al., 2023). Thus, firm's international presence could be considered to have a unique moderating effect between firm's AIC and performance:

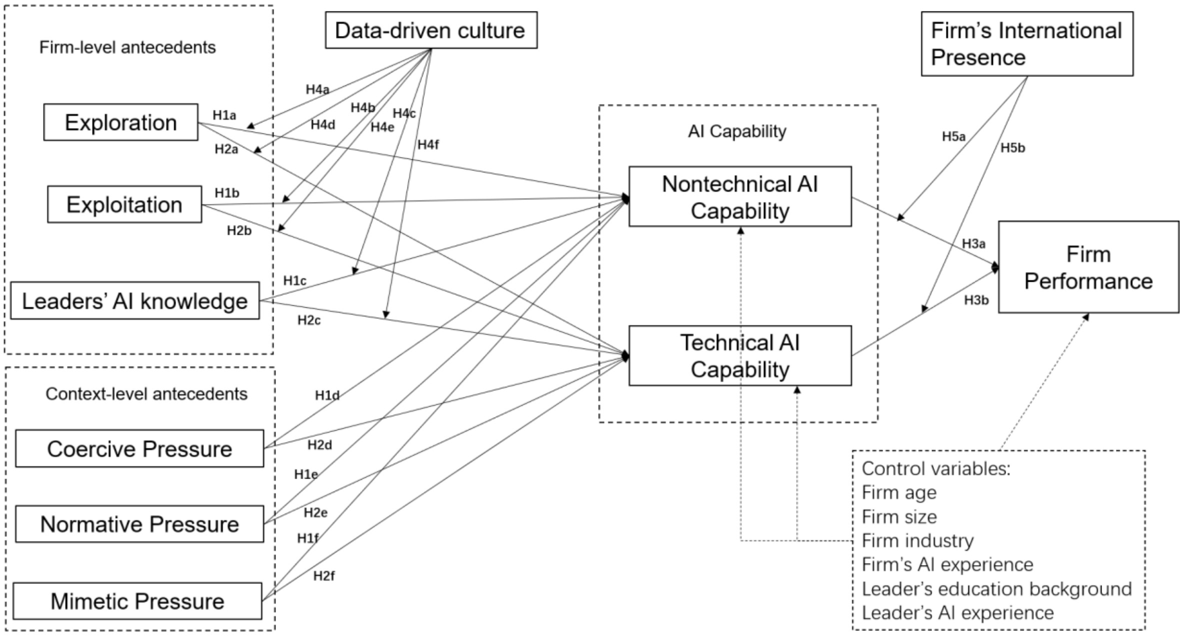
H5a: Firm's international presence enhances the relationship between its NAIC and performance.

H5b: Firm's international presence enhances the relationship between its TAIC and performance.

3.5 Conceptual framework

Combining the literature arguments and the above assumptions, this study finally forms the conceptual model as shown in the figure 3.1 below. This model describes the relationships between the main variables involved in this study. Based on RBV and institutional theory, this study will test the model to explain the impact of different antecedents on firm AIC, the impact of firm AIC on its performance, and how these impact relationships are moderated by relevant variables. In particular, AIC plays a key role in this conceptual model because it is the mediator of all other variables.

Figure 3.1: Conceptual model



3.6 Chapter summary

This study believes that internal (exploration/exploitation, leaders' AI knowledge) and external (institutional pressure) driving factors facilitate firms to allocate key resources to develop AIC (including NAIC and TAIC) and gain competitive advantages (improving firm performance). Published research results confirm the feasibility of combining RBV and institutional theory (Bag et al., 2021). The resources of AIC extracted from RBV help construct the new concepts of NAIC and TAIC, and the influence of contextual forces is demonstrated using institutional theory. However, there are few studies on the direct influencing factors of AIC and how the relationship between AIC and firm performance is moderated by some variables. The purpose of this study is to contribute to the growing body of AI and management research by filling a gap in the literature and extending existing theory. This chapter integrates relevant theories and hypotheses to establish a conceptual model of the relationships between firm's exploration/exploitation, leaders' AI knowledge level, institutional pressure, AIC (including NAIC and TAIC), and performance. Moderator data-driven culture is introduced to examine its impact on the relationship paths between firm-level antecedents and AIC, and another moderator firm's international presence is introduced to examine its impact on the relationship paths between AIC and firm performance. The next chapter will describe the research methods used in this study to empirically test this conceptual model.

Chapter 4: Research Methodology

4.1 Introduction

To work on the objectives and hypotheses of this study, developing a comprehensive research methodology is critical. It not only guides on how to test hypotheses, but also helps achieve the research aims. Research methodology refers to the theory that underpins a researcher's methods of collecting and analysing data (Hair et al., 2010). This chapter is divided into seven parts around the research methodology to clarify the design and implementation of the specific empirical research process. The first part explains the philosophical foundation and positivist stance that underpins this study. The second and third sections respectively outline the research approach and method/type selected for this study. Section 4 discusses the regional context of the selected research scope. The fifth part explains in detail the questionnaire design process and sample scope chosen for this study. Section 6 introduces the measurement tools for the variables involved in the conceptual model. Section 7 describes the pilot test and related modifications of the questionnaire, the data collection procedures for the formal survey, and the validity and reliability of the data collected.

4.2 Research Philosophy

When exploring the field of management studies, a major challenge is the complexity of social issues. Problem solving requires in-depth theoretical analysis as well as interactive investigation with people, which was emphasized in the book by Saunders et al. (2009). To cope with this complexity, researchers have developed the concept of “research philosophy,” a framework through which the development process of knowledge and its intrinsic nature can be explored. Choosing an appropriate research philosophy is crucial for researchers, as it relates not only to how they interpret their academic perspectives but also to the underlying principles on their research methods and strategies that support those perspectives. As Saunders et al. (2009) demonstrate, understanding the philosophical orientation of the study is key to determining the best research methods. In addition, Denzin and Lincoln (2011) propose that the research paradigm provides basic beliefs for the worldview and research information, and it provides guidelines for ethics, epistemology, ontology, and methodology. Therefore, research philosophy is not just a methodological choice, it also involves the researcher's overall worldview and research assumptions. By discussing the two main research philosophies, ontology and epistemology, the researcher can gain a deeper understanding of the nature and possibilities of this study. Ontology is concerned with the nature of research and ways of being, while epistemology explores the acquisition and understanding of knowledge. Both provide researchers with a solid theoretical foundation to carry out their work and find effective ways to address complex social problems in management research.

4.2.1 Ontology and epistemology

Exploring the nature of existence is the core goal of ontology, which originates from the questions of what existence is and the way of existence. The focus of ontology research is on an in-depth understanding of the nature of reality and social existence, which is also stated by Saunders et al. (2009). From a subjectivist perspective, ontology holds that social phenomena are the result of people's perceptions, as well as the social factors and actions triggered by these perceptions. In other words, what people think of as reality is actually constructed based on their assumptions. Objectivism holds a different view, which believes that social entities indeed exist in the real world. Ontology here embodies a realist philosophy, that is, there is a reality in this world that people know and is independent of human perception. This reality is determined by eternal and unchanging natural laws (Bhaskar, 2008). In the research process, ontology can be used as a starting point for a theoretical framework, especially in the position of realist ontology, which assumes that there is a reality that exists objectively and independently of human perception and can be studied empirically. This perspective is particularly important for studying the relationship between firm performance and related constructs because these constructs can be measured through empirical methods (Krueger et al., 2000). A realist perspective facilitates research because it allows researchers to examine cause-and-effect relationships and to identify patterns and trends that can be generalized to the broader scope (Sayer, 2000).

Epistemology is another important line of research philosophy that focuses on how individuals understand the world and construct and communicate knowledge in terms of its nature, possibility, scope, and foundation (Saunders et al., 2009). From another point, epistemology is an objectivist perspective that encourages researchers to observe and understand problems in the real world from their own different perspectives, including experience, background, and education. The content of epistemology mainly includes the composition, formation and dissemination of knowledge, which is its most important aspect (Pittaway, 2005). Regarding epistemology, there are two different insights in management research, namely the two philosophical approaches of positivism and interpretivism (Saunders et al., 2009). Positivism attempts to discuss and predict a series of causal relationships, while interpretivism refuses to find and determine causal relationships and laws in social phenomena. In general, epistemology provides researchers with a basis for understanding the world and constructing knowledge, and it also provides methods and frameworks for research problems. In fact, the collection and interpretation of research data is an important aspect of the practical application of epistemology.

4.2.2 Positivism and interpretivism

In social sciences, philosophical traditions have had a profound impact on research methods and theory building. Positivism and interpretivism are two core philosophical traditions (Robson, 1993). Positivism emphasizes observation and experimentation, pursuing verifiable facts and universal laws. Interpretivism focuses on understanding the meaning and motivation behind human behaviour. In order to deeply understand how these philosophical traditions shape social science research, it is necessary to discuss these two main paradigms and analyse their respective theoretical foundations, research methods and contributions to the fields. Through this discussion, the complementarity and difference between positivism and interpretivism in solving problems can be revealed, and the understanding of social science research can be further enriched.

Positivist research is a hypothesis-based research philosophy proposed by Saunders et al. in 2009. This philosophy believes that researchers can study the world objectively without affecting the research phenomena. The positivist perspective holds that credible data and facts can be derived from observed phenomena. Additionally, it emphasizes the use of highly structured methods and quantifiable findings to ensure that results are replicable. In the field of management studying AI, the positivism paradigm has proven to be suitable (Hendriksen, 2023; Nguyen and Malki, 2022). However, positivists often encounter difficulties in applying the variables in their theories. When the phenomenon under study and the data collected are inconsistent, the ability to test the theory is reduced. Therefore, pure positivism is difficult to achieve in management research. Nonetheless, quantitative research has had great success in incorporating positivism. The degree of validity, dependability, and rigor with which quantitative analysis is carried out may be used to assess the quality of research (Guba and Lincoln, 1994). Quantitative research is a very useful research method in situations where variables need to be quantified and hypotheses tested.

Interpretivist epistemology emphasizes that in order to deeply understand human behaviour, researchers must fully recognize the differences in human roles in social action (Saunders et al., 2009). This philosophical perspective views reality as a social construction, and researchers need to uncover the deeper meaning behind this construction through interaction with the respondents. Interpretivists believe that such interaction is the only way to achieve true understanding, and they reject the idea of objective knowledge independent of human thought and reasoning. In today's increasingly complex and ever-changing business environment, interpretivism has shown its strong applicability in the fields of business and management research, such as organizational behaviour, marketing, and human resource management (Goldkuhl, 2012; Myers, 2019). Saunders et al. (2009) and Charumbira (2013) also agree that interpretivism can effectively deal with the challenges in these fields. However, interpretivism has also received some criticism, mainly focusing on the lack of research generalizability and scientific rigor (Denzin and Lincoln, 2011).

4.2.3 Research philosophy adopted for the present study

This study mainly follows the principle of positivism and aims to deeply explore the specific antecedents and impact of firm AIC improvement. During the research process, data collection and interpretation are based on objectivity to ensure the authenticity and reliability of the research results. The research focuses on the causal relationships between different constructs, and verifies or refutes relevant hypotheses through a combination of theoretical analysis and empirical testing.

Specifically, in the process of exploring knowledge, positivist epistemology advocates that experience and objectivity are crucial (Killam, 2013). This epistemology believes that the establishment of knowledge must be based on observable phenomena and its validity must be verified through empirical testing. This concept is applicable to the study of the interrelationship between AIC and firm-level variables (Hendriksen, 2023; Nguyen and Malki, 2022). This study strives to apply positivist epistemology to establish a rigorous, evidence-based framework for understanding the connections between these constructs and to ensure that the findings are based on actual data and applicable to the wider business fields (Hair et al. al., 2010). In explaining the relationship between variables, the goal is to verify the proposed hypotheses. Through quantitative analysis, researchers can pursue objectivity in the research. This study also aims to demonstrate causal relationships between variables through a framework based on existing literature. The research uses a deductive approach (which will be discussed in the next section), which means that the collected data are statistically analysed to reveal causal links between variables. The researcher hopes to achieve generalization through statistical probability, that is, collecting data from large populations. When conducting research, researchers rely on concrete data and facts. Within this framework, they view organizations and other social entities as entities similar to physical objects and natural phenomena. This perspective helps ensure the rigor and reliability of the research, while also providing the possibility for generalization of the theory.

From an ontological perspective, researchers cannot have a comprehensive and in-depth look at things due to the interference of human factors. During the research process, it is inevitable to observe the truth in an incomplete and probabilistic way. Howell (2013) mentions that the complexity of reality often exceeds the ability of researchers to identify and measure reality in a completely unbiased way. In other words, reality cannot be fully understood because any investigation will be affected by the observations, mindsets and perspectives of the participants. This effect also stems in part from the adoption of Likert scales which rely on the judgment and perception of the survey subjects. This means that the research results highly depend on the subjective judgment of the subjects, making the results somewhat probabilistic. Therefore, the existence of such probability should be noticed and measures taken to reduce its impact on the research results.

Axiology is significant in exploring values and their role in academic research (Hartman, 2011). This study is founded on the principles of objectivity and value-neutrality, which are closely linked to positivist epistemology and realist ontology as well (Bryman, 2008). In order to maintain this stance throughout the research, the researcher adopts a series of precise measures, including standardized measurement tools (Cao et al., 2021), executing rigorous data collection processes (Bryman, 2008), and applying sound statistical analysis methods (Hair et al., 2010). These efforts ensure that the research results are as free from personal values and biases as possible. The goal is to obtain high-quality, trustworthy, and generalizable insights into the antecedents of firm AIC and its impact on firm performance.

Taking these various research philosophies into consideration, this study adopts the three: positivist epistemology as the mainstay, ontology and objective value theory as the supplementary support, which provides a solid guarantee for the depth and breadth of the research. The application of positivist epistemology means that research relies on empirical methods to reveal the complex relationships between variables, which enhances the positivism and operability. In addition, the introduction of ontology can treat abstract constructs as objective phenomena for in-depth discussion, which not only broadens the research horizons, but also makes the research results more convincing. The standpoint of objective value theory provides clear guiding principles for this research process, that is, adhering to objectivity and value neutrality in the process, which also enhances the validity and reliability of results. These three philosophies are highly consistent with the goals of this study. Together, they build a rigorous and systematic analysis framework and lay the foundation for investigating the relationships between AIC and other variables.

4.3 Research approach

4.3.1 Inductive and deductive approaches

The inductive approach is a bottom-up, starting from the underlying data and gradually developing a theoretical framework (Cramer-Petersen et al., 2018). Unlike traditional top-down approaches, researchers do not rely on existing theoretical systems when using inductive ways. This is mainly because existing theories may not be applicable to the research context, or new phenomena need to be explored during the research rather than just validating empirical experiments (Saunders and Townsend, 2016). By identifying key themes in the data, researchers are able to develop new theories.

In contrast, under the current research context, deductive approach is more appropriate for developing hypotheses. Relying on existing theoretical systems, researchers can better understand the research phenomenon and thus propose more accurate and targeted hypotheses (Cramer-Petersen et al., 2018). At the same time, deductive reasoning also helps to verify existing theories and provide support for the improvement and development of the theoretical system. In this process, the literature review not only provides researchers with various theoretical foundations and research methods as support, but also helps them identify and determine the key elements that need to be considered in the research model. Based on the theory and literature, researchers can collect empirical data (Lautenbach et al., 2017). The deductive approach is also characterized by starting from premises and assumptions and arriving at conclusions and recommendations through logical reasoning. These conclusions and recommendations are based on evaluated and tested assumptions, which themselves are the results of ongoing refinement in other reasonable circumstances. Using the framework of existing theory, researchers can establish causal relationships between variables. These are key points for the deductive method to play a role in research (Kase et al., 2011).

4.3.2 Research approach used in the present study

This study adopts a deductive approach, mainly using and extending RBV to test the relevant variables of AIC. In addition, this study further enriches the theoretical framework based on institutional theory and other related theories. This study is going to reveal the causal relationships between different constructs and to verify these causal relationships through empirical evidence. In terms of research methodology, it follows the positivist research paradigm and adopts quantitative research methods, which will be discussed in detail in the next section. The goal of this study is to demonstrate cause-and-effect relationships and provide generalized conclusions based on data collected from a number of firms using AI techniques. It is based on RBV and institutional theory, combined with Mikalef and Gupta's (2021) conceptualization of AIC, to further analyse the internal and external factors that affect firm AIC, as well as the impact of AIC on firm performance. Through these analyses, it is expected to provide valuable insights into the application of AI in business and management.

4.4 Research Methodology

In social science research, there are two main research methods: qualitative and quantitative research. These two methods play different roles and each has its own unique research logic. On one hand, qualitative research is based on an inductive approach. Researchers will start from specific facts and cases and refine general theories or concepts through observations and interviews. Qualitative research focuses on deep understanding and explanation of phenomena and usually does not require large samples, but does require in-depth case studies. This research method is important in sociological research, especially when it is necessary to understand complex social phenomena and individual behaviours. On the other hand, quantitative research is based on a deductive approach. This means that researchers will start from general theories and use data and statistical analysis to verify or falsify these theories. Quantitative research usually requires large samples to ensure the generalizability and reliability of the results. This method is also widely used in sociological research, especially when it is necessary to quantitatively describe and analyse a certain phenomenon. In general, quantitative and qualitative research methods both have unique advantages and limitations and can provide valuable insights (Bell et al., 2022; Saunders et al., 2009).

4.4.1 Qualitative research method

Qualitative research method is to build a complex and comprehensive understanding through in-depth exploration of social or human issues (Gray et al., 2007). The goal of this research method is to collect information with a high level of detail and present it in the form of words rather than numbers. In qualitative research, researchers typically adopt an inductive approach and rely heavily on qualitative data (Jonker and Pennink, 2010). One of the main benefits of qualitative research is that information is gathered in settings similar to a particular circumstance instead of using extensive questionnaires or interviews. This makes it possible for qualitative data to draw attention to a particular instance or internal workings within a case and place it inside a particular setting. Qualitative research reveals the complexity of social and human interactions in natural settings because of the detailed quality of the data. Additionally, since data production is flexible, researchers may utilise the data for any process and, in some rare circumstances, even evaluate causal linkages (Miles and Huberman, 1994). Qualitative research is constrained, however, in part because it often gathers data on a small scale and develops or advances ideas based only on a thorough comprehension of a particular phenomenon rather than on conclusions that can be applied generally. According to some researchers, qualitative research may lose its legitimacy in terms of validity, reliability, and generalisation if it lacks a scientific foundation and improper data processing and interpretation (Denzin and Lincoln, 2011), which is also supported by positivist philosophy.

4.4.2 Quantitative research methods

The core of quantitative methods lies in the in-depth mining of numerical data, the use of statistical and mathematical techniques to explore the interaction between different variables, and then scientifically verify the validity of specific hypotheses (Yilmaz, 2013). The significant advantage of this method is that the data it relies on are highly reliable and time-efficient, making it suitable for large-scale surveys and able to quickly collect the required information from many respondents. However, these advantages of quantitative research also bring certain limitations of their own (Choy, 2014). For example, in order to obtain valid research results, researchers need to design appropriate collection tools and ensure the effective distribution. In practice, however, researchers may encounter situations where they are unable to obtain a sufficient sample, depending on the willingness of potential respondents to participate in the study. In addition, another problem mentioned by Dudwick et al. (2006) is that researchers may lack the necessary expertise in quantitative data analysis, which will affect the accuracy of the study. Quantitative methods also rely on a deductive approach and thus rely on a predetermined set of standardized responses, which does not allow respondents to freely verbalize their feelings, opinions, and experiences. When quantitative researchers remain neutral throughout the research process, it also means that participants' personal meanings and understandings of the research phenomenon are ignored (Patton, 2002).

4.4.3 Mixed research methods

In research, complex research questions are sometimes faced that cannot be answered solely by quantitative or qualitative methods. This is when mixed methods are particularly important. Mixed methods can combine the strengths of quantitative and qualitative research to help provide a more comprehensive and in-depth understanding of the research problem. The advantage of using mixed methods is that it not only allows for the evaluation of patterns in the numerical data collected but also allows for a deeper understanding and elaboration of certain information. Mixed method is a powerful research tool that provides more accurate and richer answers to scientific research (Jick, 1979; Strijker et al., 2020).

4.4.4 Research method used in the present study

Quantitative method is chosen for this study. This choice is based on available resources as well as the relative effectiveness of quantitative methods in producing the necessary information (Peterson et al., 1982). In the research field of AI and business management, both quantitative and qualitative research methods have played an important role and together provided rich insights to the field (Di Vaio et al., 2020). The purpose of this study is to test the relationships between AIC and other related research variables. To achieve this goal, quantitative methods are considered the most suitable. In addition, the methodological choice is consistent with most current management research on AI. Review on the relevant research shows that most empirical studies in this field published in mainstream academic journals favour quantitative methods, which collect large data sets from survey scales. However, when using quantitative methods, researchers must also be aware of the limitations. As in the previous discussion, most quantitative studies rely on questionnaires to collect primary data, and this single method of data collection may lead to questions about objectivity due to potential common method bias (Podsakoff et al., 2003). This study collects quantitative data on firms using AI techniques in China, aiming to test the conceptual framework and accept or reject hypotheses on the basis of numerical data. With this method, it could be able to provide more precise and empirical insights into the application of AI in management.

4.5 Research Context

Appropriate research methods should match the essential characteristics of the research and most effectively promote the achievement of the research objectives (Bell et al., 2022). This logic applies not only to the choice of research methods, but also to the choice of research context. Therefore, it is necessary to explain why China, especially the Yangtze River Delta region of China, is chosen as the geographical background of this study. This section discusses how this region provides a unique perspective and valuable data resource for the research.

4.5.1 Why study firm AIC in China

China is a worldwide leader in the deployment of AI techniques, according to recent research from the Centre for Data Innovation (Castro and McLaughlin, 2021). This achievement is supported by reports from multiple research institutions, all of which show that China ranks first in the world in the number of AI publications (China Science and Technology Policy Institute of Tsinghua University, 2018; Stanford University, 2021; Zhang, D. et al., 2021). The Chinese Academy of Sciences is especially noteworthy since, being the first publishing organization in the world devoted to AI subjects, it has published over 26,000 articles by the year 2017. Furthermore, the Chinese Academy of Sciences holds the second position in the list of highly referenced publications within the AI area. This demonstrates even more the scope and depth of Chinese AI research. These achievements not only demonstrate its huge academic influence, but also reflect China's leading position and its strong strength and sustained development potential in the field of AI.

Since the 2000s, the Chinese government has played a pivotal role in China’s successful development of AI. It provides universities and research institutions with abundant funding to support AI research and makes significant investments in telecommunications infrastructure. These measures have laid a solid foundation for the development of AI techniques and applications in China. For another thing, China has the largest population in the world, which reaches 1.4 billion. This provides a huge market for the application of AI. In addition, the popularity of mobile phones in China has been impressive (from 2010 to 2020, the number of users surged from 300 million to 900 million). This phenomenon has further promoted the popularity of the Internet and 4G in China, causing a large amount of data to be generated and stored. According to statistics, China's data circle (which means all the data created and replicated in one year) is growing 3% faster than the global average. By 2018, China's total data accounted for 23.4% of the world's total data, up to 7.6 zettabytes. This huge data resource provides prerequisites for China to vigorously develop AI applications.

In December 2017, China took an important step to promote the development of the new generation of AI industry and released the “Three-Year Action Plan to Promote the

Development of a New Generation of AI Industry 2018-2022”. This plan is closely integrated with the "Made in China 2025" strategic plan and clarifies the specific tasks for the development of a new generation of AI. It aims to accelerate the deep integration of information technology and manufacturing technology. By commercializing the new generation of AI technique, it will be promoted to enhance its deep integration with the real economy. China’s achievements in AI applications are also very impressive. According to research by Xiao and Liu (2019), when it comes to the use of AI in manufacturing, finance, education, medical imaging, and other sectors, China has shown notable benefits. AI has emerged as the primary strategic focus for firms in the Internet technology space. Many of the technical innovations created, including iFlytek's voice recognition and Baidu's face recognition, are at the forefront of the global technology market. In terms of AI patent applications and associated fundamental R&D activities, the United States and China continue to lead the world, according to the World Intellectual Property Organization's (WIPO) 2019 report. China also has advantages in terms of developing DL technology (Wang et al., 2018). Face recognition is being used in everyday situations to improve user experience and save time, such as facial payment in shops and information retrieval about flights at airports. The outcomes of the automated warehouse company expansion are also impressive. For instance, JingDong's Shanghai operation centre can process, choose, and deliver 200,000 orders daily with only four employees working with autonomous robots. Furthermore, the ongoing enhancement of industrial automation has provided further momentum to the growth of AI in China. According to report by International Federation of Robotics, China surpassed the combined number of robot installations in Europe and the Americas in 2018 with 154,032 deployed industrial robots.

From a firm perspective, China encourages firms to develop AI technique application scenario opportunities around the important needs of the industry and key issues of people's livelihood, such as firm intelligent management, key technology research and development, and new product cultivation. It strongly supports unicorns and AI start-ups to actively carry out scenario planning, participate in the construction of urban and industrial scenarios, and achieve business growth through scenario innovation. Local governments are also encouraged to help firms achieve breakthroughs by compiling recommended catalogues of scenario innovation results.

To sum up, China has huge data resources, advanced AI techniques and highly developed application levels. At the same time, the government vigorously promotes firms to develop and use AI-related technologies. It is a very suitable environment for conducting firm AI-related research.

4.5.2 Regional research background

The Yangtze River Delta (YRD), Beijing-Tianjin-Hebei, Pearl River Delta, and Sichuan and Chongqing are China's four major economic circles, and their economic progress has driven China's overall development (Sun et al., 2022). YRD includes three coastal provinces in southeastern China: Anhui, Jiangsu, and Zhejiang, and one city: Shanghai. YRD is one of the regions with the most active economic development, the highest degree of openness, and the strongest innovation capabilities in China, and plays a key role in the development of China's AI industry (Xu et al., 2022). There has also been previous research on business intelligence applications that takes firms in the YRD region as the research objects, which verifies the feasibility of this sample selection scope (Cheng et al., 2020).

According to the latest data from the National Bureau of Statistics of China, YRD has more than 4,000 AI companies. As of 2022, there are 356 AI technique industrial parks in YRD, accounting for 33.18% of the total number of its industrial parks. These data rank first among the four major economic circles. In addition, YRD has the largest number of AI patent applications, reaching 36,854 (Chao and Tao, 2022). A report, released by the Chinese institute of New Generation Artificial Intelligence Development Strategies in May 2023, also shows that the regional competitiveness of the YRD AI industry ranks first among the four major economic circles (Liu et al., 2023). The report conducts a comprehensive evaluation of the regional AI industry competitiveness based on six indicators: firm capabilities, academic ecology, capital environment, international openness, linking capabilities, and government response capabilities. Judging from the scores and rankings of the six indicators, YRD ranks first among the four major economic circles in terms of government response capabilities, academic ecology, and linking capabilities; it ranks second in terms of firm capabilities, capital environment, and international openness (Liu et al., 2023). In order to drive the economic transformation through digitalization and intelligence, many economically developed prefecture-level cities in YRD have relied on their scientific research and technical advantages to introduce AI-related policies and plans, thereby accelerating the construction of AI industrial parks and promoting the development of the AI industry.

Data from the 2022 Yangtze River Delta Artificial Intelligence Industry Development Report (Gu, 2023) shows that, as of September 2023, the number of Shanghai's AI policy documents increased from 37 in the previous year to 48. Compared with the high-density policy supply in other provinces and cities (for example, the number of AI policies and regulations in some provinces has doubled in one year), YRD is relatively mature in the construction of AI development systems and is more cautious when proposing new AI policies. From the perspective of AI legislation, currently only two cities in China, including Shanghai, have issued AI legislative documents. Shanghai has issued the first provincial-level local regulations on AI in China, taking the lead in legal protection of this area. The other three provinces of Anhui, Jiangsu, and Zhejiang in YRD, have also issued digital regulations and formulated relevant policies for the innovation and regulation of AI algorithms, forming a relatively complete institutional system. This has not yet been reflected in other areas of China mainland.

The high-quality development of the AI industry is inseparable from the resource support role of information infrastructure such as networks, computing power, and data (Ahmed et al., 2022). In terms of network resources, within the YRD region, Shanghai, Zhejiang, and Jiangsu have a high density of 5G base stations and strong network construction capabilities. As for computing power, China has launched a large-scale project in 2022 to build national computing power hubs in eight regions, including YRD. Serving these hubs, 10 data centres including the YRD Ecological Green Integrated Development Demonstration Zone have been planned. Therefore, YRD is also at the forefront of the country in terms of computing resources. When it comes to data resources, thanks to the acceleration of China's data platform construction, YRD has the largest number of national-level green data centres. By September 2023, there are 45 in total, including 11 in Shanghai, 17 in Jiangsu, 12 in Zhejiang, and 5 in Anhui.

Technical innovation is the dominant factor in the rapid development of AI industry (Dudnik et al., 2021). In terms of firm R&D investment, Gu (2023) sorted out the data disclosed in the 2022 financial reports of listed companies with AI concept stocks. The total R&D investment of listed companies in Zhejiang, Shanghai, and Jiangsu respectively reached 23.2 billion yuan (About 2.55 billion pounds), 9.85 billion yuan (about 1.08 billion pounds), and 9.17 billion yuan (about 1.01 billion pounds), all ranking in the top five in the country. According to statistics from data service provider ITjuzi, a total of 902 investment and financing events in the field of AI occurred in China in 2022. Among them, the number of such events in the YRD region accounted for the largest proportion among all regions, reaching 309 which was more than one-third of the total. This shows that YRD has the most active investment and financing activity in the field of AI and has received a large amount of capital support, which is conducive to its AI industry development and large-scale application of AI techniques.

In addition, since 2019, China's Ministry of Science and Technology has approved the establishment of 17 national new-generation AI innovation and development experimental zones, distributed in 15 provincial administrative regions, of which YRD occupies 5 seats. China's Ministry of Industry and Information Technology has approved the construction of 9 national AI innovation and application pilot zones. Shanghai and Hangzhou (the capital of Zhejiang Province) are among these pilot areas. About high-end talents, the number of 2022 Chinese outstanding young IS experts is 146, among which 41 are from YRD, showing that high-end AI talents are highly concentrated in this region.

The development level of AI firms in YRD is also very high, and their scale is expanding rapidly. By September 2023, there were 143 listed AI firms in YRD, which had doubled from 63 in the previous year. Shanghai has 41 listed firms, 44 in Zhejiang, 44 in Jiangsu, and 14 in Anhui (Gu, 2023). In 2023, there were more than 11,000 AI firms in China, of which 4,141 were located in YRD. This number of AI firms in YRD accounts for the largest proportion among all major regions in the country.

The YRD region also has many other excellent conditions for the development of AI. First, the region has abundant scientific research talents and higher education resources, including many world-class universities and research institutions. This provides a solid foundation for AI research and development. Secondly, YRD has a developed economy and a complete industrial chain and market system, which can provide a good innovation environment and business opportunities. In addition, it also has relatively complete infrastructure and transportation networks, which facilitate the flow of talents and resource sharing.

To sum up, the YRD region has made remarkable achievements in the field of AI by virtue of its advantages in comprehensive strength, financing amount and talent reserve. At the same time, it has a developed economy and a large population, and has outstanding advantages in firm AI technique research, development, and application. Therefore, YRD is a suitable regional scope for studying firm AIC.

4.6 Research design

4.6.1 Research strategy through survey questionnaire

A framework for varied research strategies is put out by Saunders et al. (2009) and includes a wide range of techniques, such as action research, grounded theory, surveys, archival research, action research, and case studies. Positivist and objectivist philosophies include techniques of surveys and experiments, while interpretivist and constructivist philosophies include case studies, action research, grounded theory, and archive research (Saunders et al., 2009). Bell et al. (2022) stress that selecting a research approach requires well thought out study goals and clarity. Because this study adheres to the positivist school of thought, its primary research design is an experiment or survey (De Vaus, 2013). Experimental research is a potent instrument for psychology and social science research, according to Saunders et al. (2009). The definition of an experiment is an exploratory and explanatory study intended to address "how" and "why" issues. As Chinese firms adopting AI techniques are the research subjects for this study, it is clearly not practical to perform tests in a controlled environment in real-world settings. Consequently, it becomes clear that the survey approach is a better research design for this particular topic. This method facilitates the effective collection of data from the target firms in order to assist the accomplishment of the study goals.

Surveys are a popular method for gathering data. It uses questionnaires, interviews, content analysis, and observation to gather data from certain groups. This process can generate a significant volume of quantitative data quickly and affordably (De Vaus, 2013). Furthermore, by employing a predetermined, organised set of questions, questionnaires enable researchers to gather data so they may record participants' answers and do further behavioural analysis. Bernard (2017) provides more evidence about the benefits of surveys. First of all, it can quickly produce a significant volume of quantitative data. Second, it may assist researchers in gathering data on viewpoints, descriptions, attitudes, and other topics. Lastly, it can extract data from almost any population that can be generalised. Because of these benefits, surveys are quite common in quantitative research and enable researchers to obtain data in a simple and consistent way (Bernard, 2017). According to Dawson (2018), questionnaires may also be used to gather participant data in a way that requires little interaction on the side of researchers. Generally speaking, using questionnaires for surveys is an effective and practical way to gather data, and it works well for the current study.

In this study, the researcher uses a combination of empirical and deductive investigation methods to explore the causal relationships between constructs. Specifically, the researcher uses questionnaires as the main means of collecting primary data. This method does not require researcher's significant involvement in the collection process, but can still effectively collect data from local firms in YRD. The researcher also conveys the questionnaire through relevant local government agencies to ensure the participation of AI-related firms in YRD. In summary, a survey-based research strategy takes into account the choice of data collection and is related to the research method and what is required to answer the research questions.

4.6.2 Sampling frame and target population

This study takes firms using AI technique in the YRD region of China as a sample. As discussed in chapter 4.5, China has a developed level of AI application, and YRD is the region with the most prominent technological advantages of Chinese AI firms. In developed areas, it is usually possible to obtain detailed and reliable information about the enterprise (Boso et al., 2013). Therefore, it is not difficult to establish a sufficient sample frame in a developed economic circle such as YRD. Because government agencies regularly publish documents such as the list of high-tech enterprises, the degree of information disclosure and transparency is relatively high. In China, potential challenges in collecting data are mainly related to the sensitivity of statistical data, which involves micro-level information. To this end, the researcher obtains the information of potential sample firms from various channels, especially the lists of high-tech firms disclosed by the local Science and Technology Bureau and the Industry and Information Technology Bureau. These sources provide firms' information on business names, operating locations, contact information, business activities, and ownership types. The final list of sample frames includes firms located in the multiple cities of YRD region. The firms in this sample come from various industries, including manufacturing, financial services, energy, utilities, retail, information technology, media and communication services, transportation, etc. To ensure quality responses and improve response rates, this study utilizes the key informant technique (Marshall, 1996). This technique is based on a basic assumption: key informants, due to their high status in the organizational hierarchy, are the people who know and are most familiar with the organization and are able to convey their true thoughts, opinions, and perceptions on behalf of other key decision-makers in the organization. In this study, the researcher particularly emphasizes that the people participating in filling out the questionnaire must be the most senior and knowledgeable informants or business owners themselves. This requires that the respondents must be senior managers responsible for firm strategic management and information management. Through this method, the quality and authenticity of the results are ensured.

4.6.3 Time horizon

In the research on IS, longitudinal time frames are widely adopted to gain a good understanding of IS usage behaviour at different stages (Koufteros et al., 2014). Specifically, Li et al.'s (2013) study focuses on the post-acceptance stage of IS usage behaviour. They suggest that researchers can use longitudinal research designs to observe how employees choose to incorporate certain types of innovative IS into their daily work and explore the motivations and processes behind this choice (Li et al., 2013). Furthermore, longitudinal studies are ideal for establishing causal relationships between variables and especially how these relationships evolve over time (Grublješič and Jaklič, 2015). However, longitudinal studies have their limitations. For one thing, this type of research often takes a long time to complete due to the need to collect data at different time points. For another, the long-term participation of respondents is also a challenge. Because participants may choose to withdraw due to personal wishes or other reasons during the process, which may have a negative impact on the coherence of the study and the accuracy of the results (Rindfleisch et al., 2008).

Cross-sectional studies collect data from different samples at a specific time point (Rindfleisch et al., 2008). Cross-sectional data is not suitable for time series analysis, but it does provide an effective way to examine the causal relationships of variables at a certain time (Greener, 2008). In addition, cross-sectional research allows researchers to observe and analyse a variety of different samples, which helps to obtain more comprehensive data (Koufteros et al., 2014). Ihuah and Eaton (2013) believe that cross-sectional data can be used for both qualitative and quantitative analysis, which provides researchers with flexibility. In order to conduct data analysis more effectively, statistical software such as NVivo can be used for qualitative data analysis and SPSS for quantitative data analysis (Ihuah and Eaton, 2013). This software can assist researchers in extracting valuable information from cross-sectional data and performing in-depth analysis and interpretation. Overall, cross-sectional research is a valuable research method, especially when exploring relationships between variables.

This study uses a cross-sectional time horizon. This allows data to be collected at a single time point from firms using AI technique. Besides, data is collected from multiple industries and the sample size is large. To avoid the risk of long-term participation and ensure that the study can be conducted effectively, a cross-sectional time horizon is chosen.

4.6.4 Questionnaire design

Bell et al. (2022) believe that the effectiveness of questionnaire surveys and the accuracy of the information obtained are largely affected by the design of the content, structure, and response methods of the questionnaire. In order to ensure the acquisition of valid data, the researcher designed a structured questionnaire. At the same time, according to the recommendations of Saunders et al. (2009), considering that the data collection process is completed independently by participants who do not have direct contact with the researcher, an introduction is attached when distributing the questionnaire to explain the research background and purpose of this survey. It also states that the information provided by the participants will not be misused. In addition, the researcher's contact information and expression of gratitude are also attached at the end of the questionnaire. These facilitate providing participants with the information they need to know and increase the response rate.

When designing the questionnaire, the researcher follows Krosnick's (2018) suggestions to ensure that it could comprehensively collect all the information needed to answer the research questions. Based on this, the questions/items are based on instruments that have been used and tested in previous research literature, to obtain the information needed for the constructs and variables of this study. In other words, most of the questions are adapted from the existing literature and appropriately modified for the purpose of this study. There are also few questions developed specifically for this study. When designing these questions, the researcher pays special attention to their wording and content, the format of the responses, and the order of the questions, because these are important factors that affect the quality of the answers. The researcher chooses the widely used Likert scale as the measure tool (Joshi et al., 2015). As respondents are usually unwilling to spend too much time on filling out questionnaires, the design of the scale should be as practical and uncomplicated as possible. Ultimately, most parts of the questionnaire are designed as a 7-point scale in which respondents could express their opinions by indicating varying degrees of agreement or disagreement with an item on the scale (Likert, 1932).

To conduct the survey, a questionnaire in English containing 110 questions was first designed (see Appendix 2). Since the respondents' native language is Chinese, it is necessary to translate the questionnaire, which can ensure that participants can answer accurately in the language they are familiar with. Therefore, the questionnaire was then translated into Chinese version (see Appendix 3). This translation work was completed by the researcher himself. Because the researcher also has native Chinese language ability, this ensures that each translated question is as consistent as possible with its original meaning in the English version of the questionnaire. To further improve the accuracy and reliability of translation, the researcher follows the double translation protocol view (Brislin, 1980), first translating the questionnaire from English to Chinese, and then back-translating it to English. This ensures that the Chinese version is conceptually equivalent to the original English one and minimizes translation deviations (Kim and Cavusgil, 2020). In addition, a pilot survey (chapter 4.8.1) was conducted before the questionnaire was distributed, which also provided valuable feedback for the revision of the questionnaire content and translation.

4.7 Measurement and Scales

De Vaus (2013) demonstrates that measurement is an indispensable key link in the research process, and it plays a fundamental and core role in research. First, measurement helps to theoretically expand the research premise, thereby providing a richer and in-depth perspective for the research. Secondly, measurement can transform abstract concepts into concrete indicators, which helps researchers grasp the research object more accurately, thus improving the validity and accuracy of the results (De Vaus, 2013). In research on AI in the field of business and management, measuring the constructs of AI and related variables is very complex and full of challenges (Mikalef and Gupta, 2021; Wang et al., 2023). Therefore, utilizing previously published and analysed scales is an important way to establish scale validity (Krosnick, 2018). By using these scales, the researcher can ensure the validity and reliability of this study and provide reliable measurement tools for research and practice.

According to the conceptual model and hypotheses proposed in Chapter 3, four main groups of constructs need to be measured. The first group includes the antecedents of AIC within the firm, namely exploration/exploitation strategies and data-driven culture. The second group contains the antecedents external to the firm, namely three institutional pressures. The third group consists of two constructs describing firm AIC, namely NAIC and TAIC. The fourth group contains firm performance which is the final construct of this study. In addition, the researcher asks for basic information about the surveyed firms and respondents. This is not only to ensure that the participants are the required key informants, but also to obtain relevant data on the moderating variables and control variables. The main constructs of this study are measured using 7-point Likert scales, and respondents are asked to use their experiences and perceptions to answer all questions reflecting their organizations on AIC-related variables. Table summarizes the variables used in this study.

4.7.1 Independent variables

***Exploration and exploitation strategies*.** Exploration (EXPR) is the testing of novel concepts for innovative goods, services, and technological advancements (Bierly and Daly, 2007); nevertheless, the results of exploration take longer to ascertain (March, 1991). According to He and Wong (2004) and Yalcinkaya et al. (2007), exploration is also linked to the development of new services and goods (Fischer et al., 2010). By improving on current goods and procedures, exploitation (EXPT) aims to increase efficiency in order to maximise short-term revenues and provide better outcomes (Bierly and Daly, 2007; March, 1991). This is relevant to firms that use AI techniques to boost sales, delivery, and manufacturing efficiency (Gastaldi and Corso, 2012; He and Wong, 2004).

EXPR and EXPT are measured through five statements respectively. On one hand, EXPR radically generates new knowledge through experimentation and stimulating creativity. On the other hand, EXPT increasingly enhances the existing knowledge base through efficiency and refinement (Bierly and Daly, 2007). Respondents are asked to rate each statement on a seven-point Likert scale (from 1 = “Strongly disagree” to 7 = “Strongly agree”). Regarding specific items, the researcher mainly refers to the measurements of Wang and Rafiq (2014) on organizational exploration and exploitation competences related to new product development. To better fit the research (Dillman et al., 2014; DeVellis and Thorpe, 2021), the researcher makes some adaptations on the item descriptions, such as changing “manufacturing technologies” to “AI technologies” as well as “innovation operations” to “business operations”.

Leaders’ AI Knowledge. Leader's AI knowledge can be conceptualized as a leader's expertise on smart technologies, AI, robotics, and algorithms (STARA), which can more effectively and efficiently promote organizational goals that are critical to AI implementation (Brougham and Haar, 2018; Ogbeibu et al., 2021). Brougham and Harr (2018) first proposed the concept of STARA in the human resource management literature. This concept was continued to be introduced and analyzed in subsequent related studies, confirming its effectiveness in reflecting employees' knowledge and skill levels about AI (Kang et al., 2023; Ogbeibu et al., 2021; Ogbeibu et al., 2022; Oosthuizen, 2019; Yudiatmaja et al., 2021). For organizations to benefit in the short term, enhance competitive advantage, and survive in the long term, leaders must develop their STARA competences (Masood and Egger, 2020). Organizations need leaders who can develop, manage, and deploy sensors, actuators, and IoT (smart technologies) (Haenlein and Kaplan, 2021; Li et al., 2021). The use of robots and/or chatbots has also been associated with promoting digital operations, and leaders with technical knowledge in this area are essential for managing operations (Haenlein and Kaplan, 2021; Li et al., 2021). Furthermore, research shows that in today's rapidly transforming digital world, having knowledge of AI and algorithms and the ability to implement this knowledge are fundamental to organizational growth (Sarc et al., 2019). Therefore, this study uses the STARA competence standard given by Ogbeibu et al. (2021) as a measure of leaders’ AI knowledge (LAIK), which comprises 4 items in the form of 7-Likert scale.

Institutional pressures. As mentioned earlier, there are three main types of institutional pressures. Coercive pressure (CP) is exerted by those in power, such as different government agencies or other statutory bodies (Bag et al., 2021; Chu et al., 2018). In fact, this pressure includes not only monitoring or punishing wrongdoing, but also encouraging and rewarding measures that comply with legal policies (Chu et al., 2018). Normative pressure (NP) is the pressure to ensure that firms perform organizational activities that are considered legal, or in other words, based on established expectations, shared responsibilities, and standards for performing correct actions (Jiao et al., 2022; Kuo et al., 2022). When a firm copies the organizational activities of other competitors (usually the most advantageous ones in the industry) and imitates their paths to success, this is the result of mimetic pressure (MP) (Jiao et al., 2022). In this study, three types of institutional pressure are measured using a 7-point Likert scale. The 7 statements about CP are combined with the measurement items from Dubey et al. (2019a) and Wong et al. (2020). NP and MP both have 3 statements which are from Dubey et al. (2019a) and Liang et al. (2007).

4.7.2 Mediating variables

AIC plays the role of a mediating variable in the conceptual model. It is affected by the above several antecedents and affects firm performance through its own changes. As the concepts of each AIC dimension have been discussed in Chapter 2.4, they are simply reviewed and explained below under the categories of NAIC and TAIC.

NAIC

Business skills (BS). This construct is developed to understand the business skill levels of experienced managers who are in top management positions related to business problems and direct the solutions to AI initiatives (Terry Anthony Byrd, 2000). One aspect is to assess whether managers can work with data scientists, other employees, and customers to identify opportunities that AI may bring to the organization (Gupta and George, 2016). Another aspect is to determine whether they know where to apply AI or have the corresponding leadership skills. It is also to determine the level at which managers are able to design AI solutions to support customer needs and whether they demonstrate full commitment to AI projects (Bhimani, 2015).

Inter-departmental coordination (IDC). It measures the ability of different departments within the organization (such as marketing, R&D, manufacturing, personnel) to actively cooperate, including collaboration, collective goals, teamwork, common vision, mutual understanding, shared information, and shared resources. This is closely related to AI resource integration (Soni et al., 2020).

Organizational change capacity (OCC). It is the ability of an organization to anticipate and plan for responses to internal and external changes. It is important to understand how AI can provide strategic changes to organizations and help them adapt to changing market conditions (Kearns and Sabherwal, 2006). Examples include predicting how changes in communication among organizational members could be responded to and how senior leaders will implement new values.

Risk proclivity (RP). This is the organization's ability to take bold measures to deal with project risks. This proclivity requires the organization not only to identify and exploit potential opportunities, but also to adopt an active stance to maximize the benefits of these opportunities (Scherer, 2016). To gain insight into this tendency, reflective questions are used to assess its impact on high-stakes projects. In addition, the structure of an organization also directly determines its ability to make bold and broad-based decisions, which is one of the key factors for the success of risk proclivity.

TAIC

Basic resource (BR). For organizations, the basic resources required for AI initiatives mainly include two aspects: time and funding. These two together determine the intensity of an organization's investment in AI implementation. First, time is an important dimension in measuring BR. An organization needs to reasonably plan the progress of AI projects to ensure that relevant tasks are completed on time. In addition, sufficient time also allows organizations to fully test and optimize during the AI integration process, thereby increasing the likelihood of project success. Secondly, the amount of fundings is also an important measure. To deploy AI, funding is not only used to purchase hardware equipment and software tools, but also include investment in talent training, R&D activities, etc. When an organization has sufficient financial support, it can invest more boldly in AI integration and accelerate its innovation and optimization of business models.

Data. Data is one of the core resources of AI. It is measured by the collection, connectivity, and ease of access to data. Data structure is crucial because it determines the organization's ability to store, access, integrate, and analyse data, which in turn affects whether meaningful insights can be obtained from the data (Wamba et al., 2017). Research shows that organizations often face challenges when leveraging AI for data analysis, such as how to handle massive, unstructured or dynamically changing data (Campbell et al. 2020). These challenges require organizations to have strong data storage capabilities to support high-intensity analysis and to have sufficient data resources and the ability to evaluate data and estimate errors (Akter et al., 2016). Only by solving these problems can organizations make full use of the advantages of AI, gain value insights from data, and promote business development.

Technology (TECH). Technology plays a significant role in integrating AI resources into organizations. The core of technology construct is to evaluate whether an organization is equipped with the most advanced cloud-based storage and integration services (Terry Anthony Byrd, 2000). Specifically, organizations need to ensure they have access to smart GPUs, as this is critical to the computing power of AI. At the same time, the performance of the network infrastructure cannot be ignored, supporting the efficiency and scale of applications—including scalability, high bandwidth, and low latency—that are critical to the operations. Similar to the data dimension, it is also particularly important to analyse whether organizations that want to or have integrated AI have scalable data storage infrastructure, which includes data storage, processing, and analysis capabilities. Using state-of-the-art technology to protect data throughout is also key to successfully integrating AI infrastructure (Chen et al., 2014).

Technical skills (TS). It typically assesses how much knowledge and ability the human workforce possesses to deploy solutions based on AI resources (Wamba et al., 2017). These include employees' technical skills on operating systems, understanding of machine learning, mastery of technologies such as natural language processing and deep learning, the ability to analyse and process data and ensure data security, etc. TS also includes information about organized training in handling AI applications and the work experience required to complete the job.

Since the conceptual basis of AIC in this study is consistent with Mikalef and Gupta's (2021) definition, their measurement of the AIC constructs is used for this survey. NAIC includes a total of 25 statements (9 for BS, 7 for IDC, 6 for OCC, 3 for RP), and TAIC has a total of 24 statements (3 for BR, 6 for DATA, 7 for TECH, 8 for TS). 7-point Likert scales are used to measure the respondents' agreement with each statement.

4.7.3 Dependent variables

Firm performance. An organization's ability to achieve its aims and objectives is gauged by its organizational performance. According to Cho and Pucik (2005), superior organizational performance is usually characterised by profitability, growth, and market value. A significant amount of time and energy has been invested by academics in comprehending the causal structure of organizational performance and in providing an explanation for the differences in performance across rival companies (March and Sutton, 1997).

The organizational outcome of interest in this research is perceived organizational performance. Perceived organizational performance is a useful indicator of actual organizational performance, according to Oh and Pinsonneault (2007). When comparing perceived performance to actual performance, Rust et al. (1999) found that perceived performance is a more useful metric in situations when information is lacking. This study's focus is on evaluating the strategic decision-making component associated with how an organization's performance and AIC interact. In order to make an evaluation judgement about the future performance returns from current and future technical investments, performance is a subjective assessment. Perceived performance is a necessary organizational measure since the evaluation criteria for assessing returns from current and future investments are inherently unclear. Furthermore, it is more difficult to determine real performance due to the different latencies between AIC, institutional pressure, and performance. Decision-makers may thereby include intrinsic uncertainties and different adoption, deployment, implementation, and ROI (return on investment) time delays into their assessment criteria because the performance is perceived.

Because an organization's innovation performance determines its survival, measuring innovation performance is also essential (Covin and Slevin, 1990; Laursen and Foss, 2003; Laursen and Salter, 2006). Operating in a global company context requires innovation and design thinking (Darroch, 2005; Kotler and Alexander Rath, 1984). A demanding market, quick technological advancements, and fierce global rivalry are the main drivers of product innovations (Alegre et al., 2006; Bisbe and Otley, 2004).

This study chooses a suitable scale for the assessment and looks at how AIC affects firm performance (FP). FP is determined in this survey by combining the firm's financial performance, marketing performance, and innovation performance into a composite score using seven-point Likert scales (Lee and Choi, 2003; Liu et al., 2013; Wamba et al., 2017).

4.7.4 Moderating variables

Data-driven culture. Data-driven culture (DDC) is defined as the extent to which organizational members (including employees at all levels) rely on insights extracted from data to make decisions (Gupta and George, 2016). According to this definition, DDC requires members of all the organization hierarchies jointly exert a lot of effort to integrate key resources to achieve different types of functions (Kristoffersen et al., 2021). This construct adopts the five statements provided by Yu et al. (2021). The 7-point Likert scale is also used to ask respondents to indicate how much they agree with each statement.

Firm's international presence. This refers to the firm's strategic entry into foreign markets (Sun et al., 2018). In this study, the goal is to examine whether the presence or absence of the firm's overseas business moderates the effect of AIC on FP. Therefore, only whether the company operates international business (importing or exporting goods or services from abroad) is considered, but factors such as the specific size and depth of internationalization are not taken into account. So the researcher uses the items of the internationalization variable from the study by Denicolai et al. (2021). The survey mainly asks whether the participant firms import or export from abroad which reflects the firms' international presence (INT).

4.7.5 Control variables

The control variables used in this study include firm age, size, industry, AI experience, leadership setting, and leaders' (respondents) educational background and AI experience. These variables are derived from previous studies (e.g., Kristoffersen et al., 2021; Kunisch et al., 2020; Mikalef et al., 2019a; Mikalef et al., 2021; Mikalef et al., 2023; Ogbeibu et al., 2021; Rialti et al., 2019; Tihanyi et al., 2000). Literature reviews on organizational studies support that most empirical studies investigating the relationships between organizational variables employ three control variables, namely firm age, size, and industry (Rauch et al., 2009; Trailer et al., 1996). Firm age is calculated as the number of years of operation since the firm was established (Mikalef et al., 2021; Qian and Li, 2003). Firm size is mainly distinguished by the number of employees (Mikalef et al., 2021). Since the sample firms in this survey are random and involve a wide variety of industries, the classification of Kristoffersen et al. (2021) is used to include as many industries as possible in a more general way to facilitate the answer by the interviewed participants.

Furthermore, there are many other factors that control various variables in a firm. For example, a firm's AI experience (i.e., the number of years in using AI technique) affects its ability to convert AI resources into AIC and improve performance. It also controls the extent to which firms master AI technique (Mikalef et al., 2023). Additionally, the individual educational background and AI experience of the executives participating in the survey are also important. As mentioned before, the interviewees serve as key informants in the firms and represent the top management (Marshall, 1996). Their own education level, overseas study/work experience, and experience (number of years) in using AI technique will all affect the firm's AI implementation strategy (Mikalef et al., 2019a; Rialti et al., 2019; Tihanyi et al., 2000). Therefore, it is necessary to incorporate this information as control variables.

4.8 Data collection process

4.8.1 Research ethics and approval

The survey participants are firms using AI technique in the YRD region of China. Prior to data collection (including pilot test), the researcher submitted a research plan and data collection application to the Brunel University Research Ethics Committee (REC), which were reviewed and approved. The researcher has important responsibilities, including ensuring that the dignity, rights, privacy, safety, and welfare of individuals participating in research are safeguarded. REC conducts a rigorous review of the research documents to ensure that it meets the rigor of scientific research and the requirements of ethical values. As recognition, REC issued the Research Ethics Approval to the researcher, proving that this study would comply with the policies and regulations of both the Chinese and British governments and relevant institutions.

In addition, when distributing the questionnaire, the researcher informed the participants of the background and purpose of this study and provided contact information. Meanwhile, the researcher ensures that the survey data is strictly confidential and will not share any information that violates legal ethics to third parties.

4.8.2 Pilot testing

To ensure the validity of the questionnaire used in this study, the researcher conducted a pilot testing procedure. Pilot testing is a preliminary step in testing a survey questionnaire using a small sample size. This process is necessary because it helps reduce potential problems and ambiguities that make it difficult for respondents to understand and answer the questions (Saunders et al., 2015). Pilot testing also provides the researcher with an opportunity to initially assess the validity and reliability of the questionnaire. The Chinese version of the questionnaire was used for pilot testing. Eight entrepreneurs and professors from related industries and fields participated in the test. These participants were asked to complete the questionnaire and provide feedback on: the time it took to complete the questionnaire (whether the length of the questionnaire was appropriate); the clarity of the questions (whether there were any unclear or ambiguous questions or wordings); the validity of the questions (whether there were any questions that do not meet professional knowledge or statistical norms). Respondents were also free to give any other ideas or suggestions regarding the content of the questionnaire.

In the end, one practitioner believed that the questionnaire did not need to be modified, and the other three practitioners and four professors provided many valuable and constructive opinions on the arrangement of the questionnaire content and the design of specific questions. Based on the opinions provided by the participants in pilot testing, the researcher carefully considered all feedback and revised and improved the questionnaire accordingly.

4.8.3 Data collection process

The questionnaire was distributed online to collect primary data, and the respondents were the firms' senior executives or senior managers responsible for information management. In this data collection process, the research received strong support from local governments (such as the Science and Technology Bureau and the Industry and Information Technology Bureau). Chinese government departments have strong influence over the firms under their jurisdiction, which is reflected in policy formulation, resource allocation, and supervision. The support of local government agencies can provide guarantee for efficient data collection (Cheng et al., 2020). Specifically, government departments issued notices on their official websites and government-firm contact WeChat groups (WeChat is the most commonly used chat software in China mainland), provided questionnaire links or QR codes, and invited relevant firms to participate in filling out the questionnaire. The questionnaires were all completed through the Jisc Online Surveys platform authorized by Brunel. Any raw data obtained by the researcher was not shared with any third parties. The researcher only commits to sharing the final data analysis results and findings with local government agencies and participants.

Based on the feedback from pilot testing and formal collection, it takes approximately 15-20 minutes to complete the questionnaire. Respondents were asked to provide information about their firm-related variables (as described in chapter 4.7). In addition, respondents were also asked about: (1) their business characteristics, including firm ownership type, number of main products/services, and main types of AI technique used; (2) personal characteristics, especially their positions. The researcher emphasized that the person filling out the questionnaire must be the key informant with the best knowledge of the firm or the business owner him/herself, because he/she can provide perceptions representing the firm's key decision-makers.

In order to ensure the quality of the survey and improve the response rate, the researcher implemented two actions. First, throughout the survey process, the researcher ensured the anonymity and confidentiality of all information. This means that the identities of respondents and their organizations will be protected during data analysis and reporting (Podsakoff et al., 2003). Second, at the end of the survey, the researcher promised to share the findings with the respondents, again while maintaining complete anonymity. Such a commitment can help motivate respondents to participate more actively in research.

4.8.4 Response rate

As the questionnaire was widely disseminated through local government official websites and the WeChat groups for government-firm communication, it is not possible to figure out the exact number of firms that received the questionnaire. Based on the final results, it is certain that 810 firms filled out the questionnaire. In the end, 808 firms completely answered all the questions. Through careful screening of the responses, first, 25 firms not located in the YRD region were excluded. Secondly, firms that have used AI technique for less than one year were excluded. Because it means that these firms have only little AI knowledge and experience and their AI implementation may even have just started, so the establishment of AIC and its impact on the firm cannot be observed (Côrte-Real et al., 2019). This left 442 firms in the sample. Next, according to the suggestions of Dillman et al. (2009) and Podsakoff et al. (2003), the speeding and straightlining issues in the responses should be considered. Speeding means that the respondent takes too short a time to answer the questionnaire, which is significantly less than the reasonable time required to respond (Conrad et al., 2017). Straightlining means that respondents give the same answers to all or most of the questions in the questionnaire (Kim et al., 2019). Both of these problems reflect that the respondent did not answer seriously, so the response given was invalid. 134 responses were eliminated due to speeding (respondents completed the survey in less than one-third of the median completion time, i.e. less than five minutes) and/or straightlining (90% and above of responses having the same value) (Tóth et al., 2020). Finally, the researcher excluded 102 responses that were not completed by the requested key informants. Because some firms did not follow the requirement and instead arranged for low-level administrative or financial employees to take part in the survey. Since all questions in the questionnaire are compulsory, there are no missing values in the completed responses. So there are no responses that need to be excluded due to too many missing values (N=206). The final effective response rate of the research is 206/810=25.4%. Considering that the data collection process is all completed online and the difficulty of inviting firms to participate in surveys in China (Li and Atuahene-Gima, 2001; Tang, 2016), this effective response rate is acceptable.

4.8.5 Common method bias

In the field of IS research, common method bias has always been a widely concerned issue (Chaubey and Sahoo, 2021; Elbashir et al., 2021). This bias refers to the occurrence of spurious common variation between different constructs due to the use of the same measurement tools during the data collection process (Podsakoff et al., 2003). Specifically, when self-reporting surveys are used for data collection, respondents may be influenced by the survey questions themselves, resulting in socially desirable or inaccurate responses. In addition, potential problems with stability and understanding of the measurement tool itself can also introduce errors (Podsakoff et al., 2003). When this study used a self-reporting survey, the data on dependent and independent variables were reported by the same respondent, which may lead to common method bias. In order to solve the issue, this study followed the suggestions from

Podsakoff and Organ (1986) to test common method bias through procedural methods and statistical techniques. The survey measurement items are discussed in terms of procedural methods. Issues of item loadings and collinearity among model variables are discussed in terms of statistical techniques.

The researcher conducted a pilot test before officially starting to collect data. This was done to ensure that the survey instrument (questionnaire) conveyed the research intent effectively and accurately before it was formally used, as well as eliminating any confusion that might arise due to uncertainty about wording or content. In the questionnaire design, questions related to the independent and dependent variables are arranged separately so that respondents cannot identify specific variables or constructs and avoid their understanding of questions from being affected by preset labels. Information provided by respondents will be kept completely confidential throughout the survey. In addition, when designing the questions, there are no right or wrong answers. This is to create an open and honest answering environment and reduce the respondents' concerns. These designs also mean that respondents have no incentive to deliberately modify their responses, either to conform to social expectations or to fit the response they think researchers may expect (Podsakoff et al., 2003). This helps to collect real and natural data for the research and analysis.

In terms of statistical techniques, this study uses Harman's (Harman, 1967) single-factor test to verify whether there is common method bias in the data. The basic assumption of this method is that if there is a large amount of bias, then during factor analysis, either a common factor will explain most of the variable variation, or a single factor will be isolated (Podsakoff and Organ, 1986). In other words, the researcher should put all the variables into an exploratory factor analysis, test the unrotated factor analysis results, and determine the minimum number of factors necessary to explain the variation of the variables. If only one factor is extracted or a certain factor has a particularly large explanatory power, then it can be determined that there is serious common method bias. According to this method, it was found that the first factor accounted for approximately 29.72% of the variance, which was less than the critical value of 50% (Podsakoff et al., 2003). This result suggests that a single-factor solution does not occur and that the first factor cannot explain most of the variance. Therefore, the result indicates that this study does not need to concern about common method bias issues.

4.8.6 Content validity and instrument reliability

Content validity refers to the relevance and representativeness of the questionnaire content (Sireci, 1998). The content needs to reflect the characteristics to be measured, achieve the purpose of the survey, and well represent the content to be measured and the extent to which it elicits the expected response (Fitzpatrick, 1983). The evaluation of content validity is mainly carried out through empirical judgment, usually considering three aspects (Davidsson et al., 2010): (1) whether the items measured really belong to the field that should be measured; (2) whether the items included cover all aspects of the test field; (3) whether the proportion of questions is appropriate. There are three commonly used methods to evaluate content validity. One is the expert method, which involves asking relevant experts to analyse and make judgments on whether the questions are consistent with the original content range to see whether they are a good representation of original content. The second is the statistical analysis method, that is, two sets of questionnaires are extracted from the same content and tested on the same group of respondents respectively. The correlation coefficient of the two questionnaires can be used to estimate the content validity. The third is to calculate the correlation between a certain question and the total score after removing this question, and analyse whether it needs to be eliminated (sensitivity analysis) (Yaghmaie, 2003). The questionnaire of this study is based on literature review, using concepts and items that have been tested in previous research to design variables, constructs, and measurement instruments. The questionnaire has been through the pilot test. Modifications were made based on the input of knowledgeable and experienced experts in the field. Therefore, the content of the questionnaire can be considered valid.

Among many reliability measurement methods, Cronbach's alpha coefficient is widely recognized and used because of its accuracy and convenience, which can effectively evaluate the internal consistency between various items in the questionnaire (Bryman, 2008). The value of Cronbach's alpha ranges from 0 to 1. The higher value indicates the better internal consistency of the instruments. It is generally acknowledged that when the Cronbach's alpha value is above 0.9, the reliability is very excellent; when it is between 0.8 and 0.9, the instrument has a high reliability; when it is between 0.7 and 0.8, the scale has a considerable reliability; if the coefficient does not exceed 0.7, the internal consistency reliability can be considered insufficient (Cronbach, 1951; Diamantopoulos et al., 2012). The critical element of sample size cannot be overlooked as well. According to Hair et al. (2010), Cronbach’s alpha usually shows a higher level when there is a larger sample size. Therefore, researchers should fully consider the potential impact of sample size on internal consistency and try to ensure an adequate sample to obtain a more reliable Cronbach's alpha coefficient (Hair et al., 2010). Cronbach alpha results for the constructs of this study are reported in the data analysis section (chapters 5.3 and 5.4).

4.9 Chapter summary

This chapter first clarified the philosophical foundation underpinning this study and explained the positivist stance it adopted. The positivist stance emphasizes observation and experimentation based on facts and data, thus ensuring the objectivity and validity of research. Next, the research approach, method, and type selected for this study were outlined, which were important for collecting data and carrying out the research. The regional context of the chosen area was then discussed in depth. This part is crucial to understanding the overall environment of the research subjects and helps to better interpret the data and results. Then the design process of the questionnaire mainly used in the survey and sample scope were explained in detail. Questionnaire design is an important part of the research process, and it is directly related to whether the researcher can obtain effective information from the data. Afterwards, measurement tools for the variables included in the conceptual model were introduced. The reliability of the results can be ensured by accurately measuring and evaluating the variables. Finally, the data collection process was described, including the pilot testing and related modifications of the questionnaire, and the data collection procedures for the formal survey. The validity and reliability of the collected data were also discussed to ensure its persuasiveness in preparation for the subsequent data analysis.

Chapter 5: Data Analysis

5.1 Introduction

This chapter reports in detail the results of the questionnaire from 206 sample firms and conducts in-depth analysis of the collected data. The main purpose of this chapter is to test the proposed research hypotheses and conduct an empirical evaluation of the research objectives after validating the measurement scale. The analysis process is divided into the following steps. First, the characteristic information of the sample is summarized through statistics. Then, a confirmatory factor analysis method is used to select and analyse the items, and the reliability and validity are rigorously tested to prepare for the subsequent structural equation modelling (SEM) analysis. Pearson's correlation method is also adopted to test the relationship between each construct. Finally, SEM is used to test and evaluate the research hypotheses in the conceptual framework one by one. The entire data analysis process is conducted using the SPSS 26 statistical software package to ensure the accuracy and reliability of the analysis results.

5.2 Characteristics of the Sample

The frequency of all the background information data about the sample firms and the respondent, provided in their responses, was counted. Table 5.1 shows a summary of the frequency of these data. Overall, the sample is evenly distributed in terms of age, size, product and business diversity, and the experience and choice in using AI techniques. The sample covers firms in a variety of industries. The leaders represented by the respondents also have various characteristics. According to the analysis in Chapter 5.3.3 below, the sample data is normally distributed as a whole. In addition, the sample firms come from China's YRD region with highly developed AI application level (as introduced in chapter 4.5). Therefore, the sample firms can be considered very representative. The characteristics of the sample are described in detail below.

Table 5.1: Characteristic information of sample firms and respondents

Item	Answer	Frequency	%

Age	≤3 years	25	12.13
	4-10 years	73	35.44
	>10 years	108	52.43
Number of employees	1-9	13	6.31
	10-49	46	22.33
	50-249	71	34.47
	250 +	76	36.89
Industry	Manufacturing	111	53.88
	Service provider	16	7.77
	Consultancy	1	0.49
	Financial services	5	2.43
	Energy， utilities and resources	3	1.46
	Retail and consumer goods	58	28.16
	Information technology	1	0.49
	Media and communication services	3	1.46
	Transport	8	3.88
Main business	Production	95	46.12
	Service	51	24.76
	Both	54	26.21
	Neither	6	2.91
Number of products/services	1-3	28	13.59
	4-6	61	29.61
	7-10	29	14.08
	>10	88	42.72
Ownership type	State-owned	27	13.11
	Privately-owned	155	75.24
	Collectively-owned	5	2.43
	Foreign-invested	19	9.22
Belong to a parent company?	No	149	72.33

	Yes, it belongs to a China-based parent company	41	19.90
	Yes, it belongs to a UK-based parent company	0	0
	Yes, it belongs to a non China/UK-based parent company	16	7.77
International presence	Yes, it sells abroad	55	26.70
	Yes, it buys from abroad	4	1.94
	Yes, it both sells and buys from abroad	57	27.67
	No	90	43.69
IT management-related positions set	CDO	20	9.71
	CTO	91	44.17
	CIO	45	21.84
	None of above positions	83	40.29
	We set other senior positions related to IT management	18	8.74
Firm's experience of using AI technologies	1 – 2 years	68	33.01
	2 – 3 years	36	17.48
	3 – 4 years	17	8.25
	4 + years	85	41.26
AI used in the firm	Conversational AI	61	29.61
	Biometric AI	60	29.13
	Algorithmic AI	104	50.49
	Robotic AI	97	47.09
Respondent's position	CEO/President	30	14.56
	CDO	6	2.91

	CTO	12	5.83
	CIO	6	2.91
	Director	14	6.80
	Manager	84	40.78
	Others	54	26.21
Respondent's education background	High school	3	1.46
	Vocational school	8	3.88
	Higher vocational college	19	9.22
	Undergraduate	105	50.97
	Vocational undergraduate	9	4.37
	Master	50	24.27
	PhD	12	5.83
Respondent's overseas education/work experiences	Yes, I have only studied overseas before	8	3.88
	Yes, I have only worked overseas before	19	9.22
	Yes, I have both studied and worked overseas before	11	5.34
	No, I have neither studied nor worked overseas before	168	81.55
Respondent's experiences in using AI technologies	No experience	32	15.53
	< 1 year	28	13.59
	1–2 years	41	19.90
	2–3 years	33	16.02
	3–4 years	19	9.22
	4+ years	53	25.73

5.2.1 Characteristics of respondent firms

It is emphasized at the beginning of the questionnaire that the term "firm" in the questionnaire refers to the respondent's strategic business unit, which is either an independent company or a subsidiary of the parent company (Dvir et al., 1993). Therefore, the below characteristics of the sample firms are illustrated also based on this description.

Age. In the sample of 206 firms, 25 (12.13%) of them are 3 years old or younger; 73 (35.44%) are between 4 and 10 years old; and more than half (108, 52.43%) of the firms are over 10 years old. Most of the firms (181, 87.87%) have been operating longer than 3 years.

Size. 13 (6.31%) firms have fewer than 10 employees; 46 (22.33%) have a number of employees between 10 and 49; 71 (34.47%) have 50-249 employees; and there are 76 (36.89%) firms with more than 250 employees.

Industry. Out of the 206 firms, more than half of them (111, 53.88%) are from the manufacturing industry. About one quarter (58, 28.16%) are from retailing. The rest are scattered around industries of service providing (22, 10.69%), transport (8, 3.88%), energy, utilities and resources (3, 1.46%), media and communication (3, 1.46%), and information technology (1, 0.49%).

Main business. 95 (46.12%) firms of the 206 are mainly engaged in the production of goods. 51 (24.76%) are providing services as their main business. 54 (26.21%) are doing both kinds of business, while few (6, 2.91%) are not involved in either.

Ownership. According to the categorizations of the ownership types of Chinese firms in previous research (Fryxell and Lo, 2001; Peng et al., 2004; Tan, 2002; Zhou and Van Witteloostuijn, 2010; Zhu et al., 2005), most (155, 75.24%) of the respondent firms are privately-owned. 27 (13.11%) are state-owned and 19 (9.22%) are foreign-invested. Very few (5, 2.43%) is collectively-owned which means the firm is owned collectively by all members of a local group, such as people residing in the areas where the firms are located (Fryxell and Lo, 2001).

International presence. In regards to the sample firms’ international business activities, more than half (116, 56.31%) have such business. Specifically, 55 (26.70%) firms sell their products/services abroad and 4 (1.94%) buy from abroad, while 90 (43.69%) do not carry out any international business. The others (57, 27.67%) have both import and export business.

Leadership setting. Respondents were allowed to choose multiple options in terms of whether the firm set senior positions related to managing digital technologies. As a result, most firms have set such positions. Particularly, CTO is the most popular position, which is set by 91 firms (44.17%). The second most popular is CIO which appears in 45 firms, followed by CDO set by 20 (9.71%) firms. 83 (40.29%) firms do not have any of these three positions. Plus, 18 (8.74%) claim they set other senior management positions related to IT management.

Experience using AI. As the exclusion criteria explained in chapter 4.8.4, only firms with AI experiences more than 1 year would be taken into account. In result, 68 (33.01%) firms have AI experiences of 1-2 years. 36 (17.48%) firms have used AI between 2 and 3 years, and there are 17 (8.25%) firms with 3-4 years of AI experience. 85 (41.26%) firms own relatively more experiences of using AI for more than 4 years.

AI techniques used. The most popular type of AI technique used by the respondent firms is algorithmic AI (105, 50.49%), which refers to ML algorithms trained with structured data, or DL neural networks able to learn from large amounts of labelled data, to enhance themselves through learning, and to complete various tasks such as classification, prediction, and recognition. Then it goes to robotic AI (104, 50.49%) which means physical intelligent robots used to perform specialized tasks in factory automation. Conversational AI (61, 29.61%) and biometric AI (60, 29.13%) gain nearly equal popularity among the sample firms. Conversational AI is defined as AI technique that understands and responds to human natural language in written or spoken form, while biometric AI refers to AI techniques such as facial recognition, speech recognition, and computer vision used for the identification, authentication, and security of computer devices, workplace, and home safety. This categorization of AI types follows Benbya et al. (2021), and each type of AI is explained in the questionnaire to help respondents understand and choose the multiple options that best suit their situations.

5.2.2 Characteristics of respondents

The respondents' background information was also inquired to collect relevant data. The questions mainly include the respondents' positions in the firms, their education background, overseas study and/or work experiences, and AI use experiences.

Respondent's positions. 30 (14.56%) respondents hold CEO (chief executive officer) or president positions in their firms. 12 (5.83%) serve as CTOs of their companies. There are 6 (2.91%) respondents each serving as CDO and CIO. 14 (6.80%) respondents have the title of director. 84 (40.78%) managers are also part of the survey respondents. In addition, 54 respondents chose "other positions." The researcher carefully reviewed the information provided by these respondents regarding their positions and found that they were actually in senior management positions within the firms. For example, some respondents filled in as "CFO" (chief financial officer) or "COO" (chief operating officer). Some respondents may not have understood the meaning of the provided options and filled in positions that have duplicate names or functions with existing options, such as "deputy general manager", "business manager", or "director of strategy department". Overall, the 54 respondents that belong to "other positions" still meet the requirement of key informants.

Education background. All respondents have high school education and above. Most of the respondents (176, 85.44%) have a bachelor's degree or above. Specifically, 105 (50.97%) hold general undergraduate degrees. 9 people have undergraduate degrees in vocational education. A significant number of 50 (24.27%) respondents have master's degrees. Another 12 (5.83%) hold doctorates. Among those with relatively low academic qualifications, 3 (1.46%) respondents have a high school degree. There are 8 (3.88%) and 19 (9.22%) people with secondary vocational and higher vocational education respectively. The reason why general and vocational education qualifications are distinguished is because China's education system is somehow special, and the differences between these two types of qualifications in China are quite large (Hanushek et al., 2017). Since education background is not the focus of this study, further details are not explained here.

Overseas study/work experiences. Respondents are very unevenly distributed in their overseas experiences. Only 38 (18.45 %) have studied and/or worked overseas before. In contrast, the majority (168, 81.35%) of respondents do not have any overseas study/work experiences.

Experiences using AI. Minority of respondents have no or little experience in using AI. 32 (15.53%) respondents report they do not have any AI-related experiences, and 28 (13.59%) have only been exposed to AI techniques less than one year. On the other hand, 41 (19.90%) possess 1-2 years of AI experience. 33 (16.02%) have 2-3 years and 19 (9.22%) have 3-4 years of such experience. Additionally, 53 respondents claim to have a relatively richer experience of exposure to AI techniques for more than 4 years.

5.3 Data screening

5.3.1 Missing values

When analysing the data, it is necessary to consider the issues of missing values (Hair et al., 2010). Missing values could occur because the respondents did not answer all the questions intentionally or unintentionally or there are some problems with data collection and storage systems. As stated in 4.8.4, only 2 respondents did not complete the full questionnaire, which have been excluded. In terms of questionnaire design, all the questions have been set as compulsory, which means the respondents have to answer all of them and then they can submit the answers. The researcher also checked through the data using SPSS software. With these considerations, there are no missing values found in the responses provided by the final sample firms (N=206).

5.3.2 Outliers

In data analysis, outliers are also a problem that cannot be ignored. They refer to individual observations in the dataset that are significantly different from other values (Leys et al., 2018). The high degree of abnormality in these values often adversely affects the rest of the data, thereby interfering with the research (Stehlik-Barry and Babinec, 2017). Outliers must be handled when analysing data. Otherwise, they may distort key relationships in the study, such as the correlation between variables X and Y or the regression model, leading to erroneous conclusions (Field, 2013).

Following the method proposed by Ho (2013), this study analyses and evaluates univariate and multivariate outliers. Univariate analysis focuses on extreme values that differ significantly from the expected overall value of a single construct. Multivariate analysis mainly identifies those odd combinations consisting of at least two structurally unexpected scores (Ho, 2013).

The researcher used SPSS 26 software for outlier detection (Ho, 2013). Univariate statistics and frequency analysis are able to identify the presence of out-of-range values and univariate and multivariate outliers in the data set. Boxplot is a standard outlier detection method (Dawson, 2011). Boxplots not only reveal the median and quartiles of a data set, but also clearly show the potential outliers. Drawing boxplots through SPSS tools can visibly evaluate the discreteness of data and the location of outliers. After careful inspection of the boxplots and distributions of each variable, no visually suspicious outliers were found. In addition, the researcher also used the Mahalanobis distance method to detect multivariate outliers (Leys et al., 2018). This method is based on statistical principles and examines the outlier by calculating the Mahalanobis distance between each data point and the mean. SPSS has a built-in calculation function for Mahalanobis distance, allowing the researcher to determine the existence of outliers based on the calculation results. The t value was approximated by calculating the Mahalanobis distance (D^2) of each observed variable using SPSS and dividing it by the number of variables involved (D^2/df). The common significance levels, such as 0.005 or 0.001 (Penny, 1996), are adopted regarding the threshold for the outliers. By converting the calculated t-values into p values, no significant values (less than 0.001) were found. This indicates that no outliers were detected in the data. In summary, there are no univariate or multivariate outliers in the collected data.

5.3.3 Normality

Normality tests mainly check the shape of data distribution and determine whether they conform to normal distribution. It is the basic premise of many data analysis methods (Hair et al., 2010). The normality test is a non-parametric test, and its basic assumption is that there is no significant difference between the population from which the sample comes and the normal distribution. Only when $p>0.05$ can the hypothesis be accepted, that is, the data conforms to a normal distribution. Measures of data skewness and kurtosis are used to determine whether an indicator meets the assumption of normality (Kline, 2008). There are two general methods for calculating skewness and kurtosis: the Shapiro-Wilk test or the Kolmogorov–Smirnov test. The former is suitable for small sample data (N≤50), and the latter is suitable for large sample data (N>50).

This study has a total of 206 samples, so the Kolmogorov–Smirnov test was used. The variables included in the conceptual model were all examined. Their results are shown in Table 5.2. It was found that most of the variable data showed non-normality problems. Only variables TAIC, DATA, and FP show obvious normality. In fact, statistical research demonstrates that although the skewness and kurtosis of the standard normal distribution are theoretically 0, this strict requirement is usually not met (Kim, 2013). In other words, in reality, it is difficult for the data obtained from questionnaires to achieve the ideal normality characteristics. However, if the absolute value of kurtosis is less than 10 and the absolute value of skewness is less than 3, it means that although the data is not absolutely normal, it is basically acceptable to be normally distributed (Brown, 2015; Kline, 2008; Leech et al., 2013). Therefore, the kurtosis and skewness information in Table 5.2 indicates that the variable data involved in this study can be considered to meet the conditions of normal distribution.

In addition, the researcher also used P-P (probability-probability) plots and Q-Q (quantile-quantile) plots to further assist in testing the normality. This is also a common and effective inspection method (Das and Imon, 2016). The P-P and Q-Q plots generated for each variable show that the scatter plot looks approximately like a diagonal straight line, indicating that the data shows normality (Das and Imon, 2016).

Table 5.2: Results of Kolmogorov-Smirnov normality test

Items	*n*	Mean	Std.	Skewness	kurtosis	Kolmogorov-Smirnov test	
						Statistic *D*	*p*
EXPT	206	5.741	0.738	-0.345	-0.110	0.132	0.000**
EXPR	206	5.498	0.932	-0.718	1.013	0.097	0.000**
DDC	206	5.896	0.738	-0.563	0.270	0.119	0.000**
CP	206	5.764	0.795	-0.587	0.193	0.117	0.000**
NP	206	5.413	1.183	-1.214	2.249	0.145	0.000**
MP	206	5.615	0.952	-0.297	-0.549	0.128	0.000**
NAIC	206	5.357	0.831	-0.411	-0.229	0.063	0.043*

BS	206	5.203	1.114	-0.593	0.036	0.100	0.000**
IDC	206	5.786	0.866	-0.554	0.198	0.112	0.000**
OCC	206	5.419	0.916	-0.471	0.314	0.082	0.002**
RP	206	5.021	1.215	-0.615	0.446	0.100	0.000**
TAIC	206	5.061	0.977	-0.365	0.175	0.049	0.272
DATA	206	5.158	1.027	-0.352	-0.002	0.055	0.127
TECH	206	5.137	1.081	-0.381	0.176	0.063	0.049*
BR	206	4.898	1.277	-0.504	0.310	0.109	0.000**
TS	206	5.050	1.209	-0.691	0.237	0.100	0.000**
FP	206	5.329	0.861	-0.325	0.287	0.044	0.417
LAIK	206	4.744	1.374	-0.544	-0.035	0.096	0.000**

* $p<0.05$ ** $p<0.01$

5.3.4 Initial internal reliability test

Reliability test refers to the degree of consistency of the results obtained when the same object is measured repeatedly using the same method, that is, the degree to which it reflects the actual situation (Cronbach, 1947). When assessing measurement reliability, three main methods are usually used: stability test, inter-observer consistency test, and internal reliability analysis (Bell et al., 2022). First, stability concerns the ability of a research method to produce consistent results over time and is a measure of how reliable a measurement method remains over time. Secondly, inter-observer consistency is achieved by judging whether different observers can reach a certain consensus. A measurement method is more reliable if multiple observers give similar results when evaluating the same object or phenomenon. Finally, internal reliability focuses on the consistency and intercorrelation among multiple measures. In practical research, multiple related data indicators are often collected. If there is a high consistency between these indicators, which means they are mutually supportive and correlated, then this measurement method can be considered to have better internal reliability (Bell et al., 2022).

Ensuring internal consistency is even more important when exploring the measurement of multiple items (Henson, 2001). For this reason, internal reliability was chosen as the test method in this study. Among the many methods to assess the internal reliability of multivariate research constructs, Cronbach’s alpha coefficient is widely used because of its efficiency and reliability, especially for those studies that adopt factor analysis (Taber, 2018). Therefore, this study preliminarily judged the reliability of the measurement items by calculating Cronbach's alpha coefficients. The results of Cronbach's alpha coefficients for all the key measurements are shown in Table 5.3.

Table 5.3: Cronbach's alpha coefficients of all the constructs (initial)

Constructs (number of items)	Cronbach α
EXPR (5)	0.838
EXPT (5)	0.824
DDC (5)	0.811
CP (8)	0.884
NP (3)	0.910
MP (3)	0.910
TAIC (24)	0.961
DATA (6)	0.888
TECH (7)	0.911
TS (8)	0.956
BR (3)	0.908
NAIC (25)	0.960
BS (9)	0.960
IDC (7)	0.942
OCC (6)	0.930
RP (3)	0.878
FP (12)	0.954
LAIK (3)	0.851

According to statistical standards (Cronbach, 1951), the alpha coefficient higher than 0.90 is generally considered to be the highest level of reliability, which means that the scale shows very good internal consistency. When the alpha value is between 0.70 and 0.90, it indicates that the scale shows good consistency in measuring the same constructs. Moderate reliability means that the alpha coefficient is between 0.50 and 0.70. This suggests that the scale has some degree of consistency, but there may be some inconsistency between items or the questionnaire may need improvement. Finally, an alpha coefficient of less than or equal to 0.50 is usually labelled as low reliability. This indicates poor consistency among the individual items of the scale, meaning the scale may not reliably measure the constructs. Referring to this standard, the Cronbach's alpha coefficients of all constructions in this study are above 0.8, indicating that they all have very good internal consistency.

Some studies have also suggested that alpha values exceeding 0.95 are suspicious because too high value may mean that the items are too redundant, which may lead to reduced validity of constructs (Diamantopoulos et al., 2012). However, according to Hair et al. (2010), the number of items in a construct also affects Cronbach's alpha value to a significant extent. When a construct has a large number of items, Cronbach's alpha value may be relatively high because they have the same degree of intercorrelation (Hair et al., 2010). Therefore, although the α values of constructs such as TAIC, TS, NAIC, BS, and FP are >0.95, these values are temporarily acceptable considering the number of items in them. The researcher will further refine the specific items of each construct in the next section and test the Cronbach's alpha coefficients of the refined constructs again.

5.4 Refinement of the Research Constructs

The refinement of construct items mainly uses the method of factor analysis. Factor analysis is a commonly used statistical analysis method (Kline, 2013) There are two main methods for factor analysis: confirmatory factor analysis (CFA) and exploratory factor analysis (EFA). The main difference between the two lies in their different uses: CFA is used to verify the relationship between known factors and items, while EFA is used to discover potential factor structures (Kline, 2013). In other words, for a complete or mature scale, studies usually use CFA to verify its validity. For those scales that are not mature enough or have not been tested, research tends to use EFA to explore the underlying structure of factors. In addition, research and experience show that the sample size required for EFA should be 5-10 times the number of scale items (Gorsuch, 2014; Memon et al., 2020; Suhr, 2006), while CFA generally requires a sample size greater than 200 (Jackson et al., 2013). Moreover, Comrey and Lee (2013) believe that EFA can achieve better analysis results only with a sample number of more than 300. Therefore, considering that this study aims to investigate 206 samples based on 16 constructs and 93 scale items, it cannot meet the analysis conditions of EFA. Meanwhile, as discussed in chapter 4.7, the scale items used in this study are all from mature scales in existing research. Therefore, this study adopts CFA to test the relationship between scale items and factors.

According to the discussion in chapter 4.7, this study involves 10 constructs (EXPT, EXPR, DDC, CP, NP, MP, TAIC, NAIC, FP, and LAIK) that use scale items, which means there should be 10 factors. The analysis results of the first CFA are shown in Table 5.4.

Table 5.4: CFA results of all factors and items (initial)

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	*z* (CR value)	*p*	Standardized factor loading (Std. Estimate)	SMC
Factor1	EXPT1	1.000	-	-	-	0.707	0.499
Factor1	EXPT2	1.044	0.112	9.327	0.000	0.699	0.489
Factor1	EXPT3	0.817	0.114	7.158	0.000	0.532	0.284
Factor1	EXPT4	1.003	0.100	10.012	0.000	0.753	0.568
Factor1	EXPT5	1.000	0.093	10.745	0.000	0.814	0.662
Factor2	EXPR1	1.000	-	-	-	0.815	0.665
Factor2	EXPR2	0.996	0.077	12.955	0.000	0.819	0.670
Factor2	EXPR3	0.889	0.076	11.768	0.000	0.759	0.576
Factor2	EXPR4	0.893	0.092	9.711	0.000	0.650	0.422
Factor2	EXPR5	0.899	0.104	8.666	0.000	0.590	0.349
Factor3	DDC1	1.000	-	-	-	0.643	0.414
Factor3	DDC2	1.059	0.140	7.584	0.000	0.600	0.360
Factor3	DDC3	0.859	0.149	5.782	0.000	0.442	0.195
Factor3	DDC4	1.219	0.121	10.112	0.000	0.864	0.746
Factor3	DDC5	1.256	0.123	10.175	0.000	0.873	0.761
Factor4	CP1	1.000	-	-	-	0.808	0.652
Factor4	CP2	1.014	0.081	12.455	0.000	0.777	0.604
Factor4	CP3	0.943	0.079	11.929	0.000	0.752	0.566
Factor4	CP4	1.012	0.077	13.153	0.000	0.809	0.654

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	*z* (CR value)	*p*	Standardized factor loading (Std. Estimate)	SMC
Factor4	CP5	1.011	0.108	9.365	0.000	0.620	0.384
Factor4	CP6	0.886	0.104	8.493	0.000	0.571	0.326
Factor4	CP7	0.933	0.094	9.925	0.000	0.650	0.423
Factor4	CP8	0.812	0.078	10.403	0.000	0.676	0.457
Factor5	NP1	1.000	-	-	-	0.868	0.753
Factor5	NP2	1.037	0.060	17.335	0.000	0.913	0.834
Factor5	NP3	0.966	0.061	15.866	0.000	0.855	0.732
Factor6	MP1	1.000	-	-	-	0.838	0.702
Factor6	MP2	0.972	0.058	16.874	0.000	0.915	0.837
Factor6	MP3	0.961	0.059	16.407	0.000	0.897	0.804
Factor7	DATA1	1.000	-	-	-	0.566	0.320
Factor7	TECH4	1.274	0.155	8.215	0.000	0.737	0.544
Factor7	TECH5	1.253	0.159	7.882	0.000	0.691	0.477
Factor7	TECH6	1.020	0.149	6.827	0.000	0.562	0.316
Factor7	TECH7	1.193	0.158	7.555	0.000	0.648	0.420
Factor7	BR1	0.956	0.142	6.708	0.000	0.549	0.301
Factor7	BR2	1.358	0.165	8.212	0.000	0.737	0.543
Factor7	BR3	1.206	0.153	7.859	0.000	0.688	0.473
Factor7	TS1	1.186	0.140	8.488	0.000	0.778	0.606
Factor7	TS2	1.094	0.132	8.292	0.000	0.749	0.561
Factor7	TS3	1.527	0.170	8.985	0.000	0.860	0.739
Factor7	DATA2	0.815	0.130	6.282	0.000	0.504	0.254
Factor7	TS4	1.540	0.169	9.118	0.000	0.884	0.781
Factor7	TS5	1.523	0.169	9.038	0.000	0.869	0.755
Factor7	TS6	1.537	0.173	8.902	0.000	0.845	0.715
Factor7	TS7	1.729	0.195	8.871	0.000	0.840	0.706
Factor7	TS8	1.600	0.184	8.687	0.000	0.810	0.655
Factor7	DATA3	0.838	0.127	6.590	0.000	0.536	0.287
Factor7	DATA4	1.064	0.142	7.486	0.000	0.640	0.409

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	*z* (CR value)	*p*	Standardized factor loading (Std. Estimate)	SMC
Factor7	DATA5	1.192	0.146	8.162	0.000	0.730	0.533
Factor7	DATA6	1.050	0.138	7.604	0.000	0.655	0.428
Factor7	TECH1	1.185	0.145	8.195	0.000	0.734	0.539
Factor7	TECH2	1.081	0.136	7.945	0.000	0.699	0.489
Factor7	TECH3	0.904	0.133	6.790	0.000	0.558	0.311
Factor8	BS1	1.000	-	-	-	0.767	0.588
Factor8	OCC1	0.736	0.066	11.150	0.000	0.724	0.524
Factor8	OCC2	0.813	0.065	12.468	0.000	0.794	0.631
Factor8	OCC3	0.858	0.066	13.000	0.000	0.821	0.675
Factor8	OCC4	0.752	0.063	12.005	0.000	0.770	0.593
Factor8	OCC5	0.713	0.069	10.293	0.000	0.676	0.457
Factor8	OCC6	0.727	0.071	10.269	0.000	0.675	0.455
Factor8	RP1	0.735	0.098	7.488	0.000	0.508	0.258
Factor8	RP2	0.757	0.080	9.476	0.000	0.629	0.396
Factor8	RP3	0.692	0.087	7.963	0.000	0.538	0.289
Factor8	IDC1	0.541	0.069	7.800	0.000	0.528	0.279
Factor8	BS2	0.995	0.079	12.657	0.000	0.804	0.646
Factor8	IDC2	0.481	0.068	7.064	0.000	0.482	0.232
Factor8	IDC3	0.513	0.060	8.514	0.000	0.572	0.327
Factor8	IDC4	0.576	0.070	8.225	0.000	0.554	0.307
Factor8	IDC5	0.533	0.064	8.394	0.000	0.564	0.318
Factor8	IDC6	0.543	0.062	8.770	0.000	0.587	0.345
Factor8	IDC7	0.576	0.066	8.703	0.000	0.583	0.340
Factor8	BS3	0.915	0.073	12.523	0.000	0.797	0.635
Factor8	BS4	1.102	0.086	12.884	0.000	0.815	0.665
Factor8	BS5	1.106	0.081	13.621	0.000	0.852	0.726
Factor8	BS6	1.032	0.074	13.860	0.000	0.864	0.746
Factor8	BS7	1.004	0.075	13.453	0.000	0.844	0.712
Factor8	BS8	1.078	0.080	13.414	0.000	0.842	0.709

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	*z* (CR value)	*p*	Standardized factor loading (Std. Estimate)	SMC
Factor8	BS9	0.958	0.073	13.159	0.000	0.829	0.688
Factor9	FP1	1.000	-	-	-	0.804	0.647
Factor9	FP10	1.044	0.077	13.573	0.000	0.812	0.659
Factor9	FP11	1.142	0.079	14.511	0.000	0.850	0.723
Factor9	FP12	1.119	0.074	15.156	0.000	0.875	0.766
Factor9	FP2	1.040	0.086	12.035	0.000	0.743	0.553
Factor9	FP3	1.117	0.078	14.313	0.000	0.842	0.709
Factor9	FP4	1.048	0.084	12.419	0.000	0.761	0.579
Factor9	FP5	1.023	0.080	12.863	0.000	0.781	0.610
Factor9	FP6	1.018	0.089	11.429	0.000	0.715	0.511
Factor9	FP7	1.006	0.085	11.824	0.000	0.733	0.538
Factor9	FP8	1.080	0.077	13.966	0.000	0.828	0.686
Factor9	FP9	1.062	0.080	13.235	0.000	0.797	0.636
Factor10	LAIK1	1.000	-	-	-	0.856	0.733
Factor10	LAIK2	1.171	0.091	12.886	0.000	0.846	0.716
Factor10	LAIK3	0.934	0.083	11.309	0.000	0.736	0.542

Note: '-' indicates that this item is a reference item.

Factor loadings show the correlation between factors (constructs) and scale items. Standard loading values are usually used to represent the correlation between factors and items (Brown, 2015). If an item is significant, that is, the standard loading coefficient value is greater than 0.7, it means there is a strong correlation. If an item does not show significance, or the loading is less than 0.6, it means that the relationship between the item and the factor is weak, and the item can be considered to be removed (Brown, 2015).

According to the preliminary results of CFA, the relationships between EXPT3, EXPR5, DDC2, DDC3, CP6, DATA1, DATA2, DATA3, TECH3, TECH6, BR1, RP1, RP3, and all IDC items and their corresponding factors are weak (<0.6). Thus, these items should be considered to be removed. The reasons for removing these items are discussed below from the perspectives of theory and research practice.

First, items EXPT3, EXPR5, DDC2, DDC3, and CP6 are related to the constructs of antecedents for AIC. EXPT3 "*(Since your company adopted AI techniques, your company has) enhanced competencies in searching for intelligent solutions to customer problems that are near to existing solutions rather than completely new solutions*" may not have clearly conveyed its original meaning to the respondents. Exploitation emphasizes improving and upgrading based on existing technology or knowledge and experience to obtain better AI resources (Jafari-Sadeghi et al., 2021). However, the expression of EXPT3 is more like a lack of ambition, because it says "rather than completely new solutions" at the end. Respondents may understand it as being asked if they are unwilling to adopt new technology. While other EXPT items have superficially more positive meanings. Therefore, EXPT3 does not show good internal consistency with the other items. Similarly, for EXPR5 "*(Since your company adopted AI techniques, your company has) strengthened technological capabilities in areas where it had no prior experience*", respondents may have thought that this item implied that their firm did not have any AI-related experience, and therefore did not provide answers consistent with the other EXPR items. As for DDC2 "*We base our decisions on data rather than on instinct*" and DDC3 "*We are willing to override our own intuition when data contradict our viewpoints*", they both ask if the respondent is willing to trust data more than their intuition. Recent research (Wu, 2022; Yu et al., 2022) has shown that though organizations in China have adopted BDA and other digital technologies, their managers still tend to rely on instinct instead of data. This could be the reason that respondents' answers did not show support for the statement of the two items. Regarding CP6 "*Regulation and policy determents support the development of innovative solutions for implementing AI techniques*", it tries to test whether coercive pressures could play a positive role in stimulating firms to implement AI techniques, which is adapted from Bag et al. (2022). However, according to its definition, CP highlights the coercive nature of this pressure and the oppression that firms feel from it, which often fails to make them motivated but more likely to be forced (Lui et al., 2021). In the original research cited, Bag et al. (2022) study the relationship between CP and eco-innovation, assuming that eco-innovation is adverse before but improved after the introduction of CP. This may not fit the situation of this study.

Second, some items related to TAIC (DATA1, DATA2, DATA3, TECH3, TECH6, BR1) also show inconsistency with the construct. According to the definition of TAIC in this study, it refers to the firm's ability to utilize AI resources that could have a direct effect on the firm's AI technical advancement. By reviewing the content of the first three items for construct DATA, they may not conform to this definition. DATA1 "*We have access to very large, unstructured, or fast-moving data for analysis*" and DATA2 "*We integrate data from multiple internal sources into a data warehouse or mart for easy access*" stress the ease with which the company has access to data. Nonetheless, having easy access to data does not necessarily mean the strong techniques acquired. In other words, it is the ability to utilize data that brings out technical progress, not the ability to obtain data (Klievink et al., 2017). Effective utilization of data requires advanced data analysis tools, algorithms and expertise (Joubert et al., 2023). Even with a large amount of data, if there is a lack of effective analysis and mining methods, the data may still not reach its potential. The acquisition of data is only a prerequisite for implementing AI techniques. Technical progress mainly relies on innovation in algorithms, computing power, model architecture and other aspects (Cyganek et al., 2016). Advances in these areas require significant time and capital investment and are not directly related to the ease of data acquisition (Joubert et al., 2023). Besides, the practical use of data is further restricted because of uncertain data quality as well as ethical and legal requirements (Janssen et al., 2020). These obstacles have to be coped with before transforming data to the resources for AI techniques. Same reasons make sense for DATA3 "*We integrate external data with internal to facilitate high-value analysis of our business environment*", which mainly emphasizes the integration of data but still ignores the analysis ability.

Concerning the other problematic items in TAIC, TECH3 "*We have invested in networking infrastructure that supports efficiency and scale of applications*", TECH6 "*We have invested in scalable data storage infrastructures*", and BR1 "*Our AI initiatives are adequately funded*" all talk about investment in AI-related resources. Again, considering the definition of TAIC, the direct relationships between these items and the technical advancement of AI are debatable. For example, investments in infrastructure are typically made to improve the availability, efficiency, and stability of resources to support the operation and development of AI technique (Pan et al., 2021). However, these investments are only to provide the necessary conditions and environment and do not directly affect the innovation and progress of the technology itself. In fact, the relationship between IT infrastructure and firm innovative capability has not been well studied (Cassia et al., 2020).

Finally, some items under construct NAIC also show internal consistency issues. RP1 "*In our organization we have a strong proclivity for high-risk projects (with chances of very high returns)*" and RP3 "*We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities*" may be clear and relevant enough based on the statements. Specifically, in respondents' view, RP may have more to do with market, financial, and managerial risks than directly with technology risks. Even if firms have a high tolerance for market risks, they may still be cautious about technology risks, which may affect their investment and development in the field of AI. Therefore, the shortcomings of item description may have caused some ambiguity. Results from CFA also suggest all IDC items should be removed. The main reason is that the distinction between the seven items is not obvious. Although Mikalef and Gupta (2021) set these seven items to measure IDC, they essentially serve the same statement. Maybe it would be better to consolidate them into one single item. In addition, previous research also finds that IDC will lead to the risk of project delay or termination, thereby increasing costs (Cuijpers et al., 2011). This may not be conducive to utilizing AI resources. Therefore, all seven IDC items are excluded.

With the above considerations, items EXPT3, EXPR5, DDC2, DDC3, CP6, DATA1, DATA2, DATA3, TECH3, TECH6, BR1, RP1, RP3, and IDC1-7 were all removed from the scales. In fact, the researcher hopes such further analysis of item removal could also contribute to the relevant theoretical development and research experiences. After conducting CFA again, it was found that CP5 also had a weak relationship with the corresponding factor (loading<0.6), so it was removed. Repeating the process, CP7 was also eliminated because the relationship was too weak. The reasons for removal of CP5 and CP7 were the same as those of CP6. Finally, all the rest items show strong relationships with the corresponding factors, as Table 5.5 illustrates.

Table 5.5: CFA results of all factors and items (final)

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	*z* (CR value)	*p*	Standardized factor loading (Std. Estimate)	SMC
Factor1	EXPT1	1.000	-	-	-	0.693	0.480
Factor1	EXPT2	1.059	0.116	9.121	0.000	0.696	0.484

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	*z* (CR value)	*p*	Standardized factor loading (Std. Estimate)	SMC
Factor1	EXPT4	1.018	0.104	9.764	0.000	0.749	0.562
Factor1	EXPT5	1.025	0.097	10.540	0.000	0.818	0.668
Factor2	EXPR1	1.000	-	-	-	0.810	0.656
Factor2	EXPR2	1.009	0.079	12.735	0.000	0.824	0.678
Factor2	EXPR3	0.904	0.077	11.696	0.000	0.767	0.588
Factor2	EXPR4	0.901	0.094	9.613	0.000	0.652	0.425
Factor3	DDC1	1.000	-	-	-	0.625	0.390
Factor3	DDC4	1.260	0.130	9.675	0.000	0.868	0.753
Factor3	DDC5	1.292	0.133	9.700	0.000	0.872	0.760
Factor4	CP1	1.000	-	-	-	0.900	0.810
Factor4	CP2	1.011	0.059	17.225	0.000	0.863	0.745
Factor4	CP3	0.871	0.062	14.103	0.000	0.774	0.599
Factor4	CP4	0.826	0.064	12.956	0.000	0.736	0.541
Factor4	CP8	0.673	0.066	10.141	0.000	0.624	0.389
Factor5	NP1	1.000	-	-	-	0.867	0.752
Factor5	NP2	1.039	0.060	17.318	0.000	0.914	0.836
Factor5	NP3	0.967	0.061	15.832	0.000	0.855	0.731
Factor6	MP1	1.000	-	-	-	0.838	0.703
Factor6	MP2	0.971	0.058	16.822	0.000	0.914	0.836
Factor6	MP3	0.961	0.059	16.387	0.000	0.897	0.805
Factor7	DATA4	1.000	-	-	-	0.615	0.378
Factor7	BR3	1.138	0.137	8.282	0.000	0.664	0.440
Factor7	TS1	1.175	0.125	9.424	0.000	0.789	0.623
Factor7	TS2	1.075	0.118	9.107	0.000	0.753	0.566
Factor7	TS3	1.539	0.151	10.210	0.000	0.886	0.786
Factor7	TS4	1.550	0.149	10.385	0.000	0.910	0.828
Factor7	TS5	1.530	0.149	10.257	0.000	0.893	0.797
Factor7	TS6	1.531	0.153	10.014	0.000	0.861	0.741
Factor7	TS7	1.712	0.172	9.936	0.000	0.851	0.725

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	z (CR value)	p	Standardized factor loading (Std. Estimate)	SMC
Factor7	TS8	1.601	0.164	9.755	0.000	0.829	0.687
Factor7	DATA5	1.133	0.130	8.718	0.000	0.710	0.503
Factor7	DATA6	0.986	0.124	7.940	0.000	0.629	0.396
Factor7	TECH1	1.121	0.128	8.729	0.000	0.711	0.505
Factor7	TECH2	1.024	0.122	8.421	0.000	0.678	0.460
Factor7	TECH4	1.195	0.137	8.700	0.000	0.708	0.501
Factor7	TECH5	1.175	0.142	8.275	0.000	0.663	0.440
Factor7	TECH7	1.082	0.141	7.663	0.000	0.602	0.362
Factor7	BR2	1.293	0.147	8.798	0.000	0.718	0.516
Factor8	BS1	1.000	-	-	-	0.802	0.644
Factor8	OCC1	0.695	0.060	11.502	0.000	0.715	0.512
Factor8	OCC2	0.762	0.059	12.877	0.000	0.779	0.606
Factor8	OCC3	0.797	0.060	13.332	0.000	0.799	0.638
Factor8	OCC4	0.693	0.057	12.092	0.000	0.743	0.552
Factor8	OCC5	0.666	0.064	10.407	0.000	0.661	0.437
Factor8	OCC6	0.672	0.066	10.244	0.000	0.653	0.426
Factor8	RP2	0.704	0.074	9.476	0.000	0.612	0.374
Factor8	BS2	0.987	0.070	14.178	0.000	0.834	0.696
Factor8	BS3	0.888	0.065	13.577	0.000	0.809	0.655
Factor8	BS4	1.086	0.076	14.356	0.000	0.841	0.708
Factor8	BS5	1.087	0.071	15.248	0.000	0.876	0.768
Factor8	BS6	1.001	0.066	15.257	0.000	0.876	0.768
Factor8	BS7	0.973	0.066	14.734	0.000	0.856	0.733
Factor8	BS8	1.043	0.071	14.641	0.000	0.853	0.727
Factor8	BS9	0.914	0.065	14.030	0.000	0.828	0.686
Factor9	FP1	1.000	-	-	-	0.804	0.646
Factor9	FP10	1.044	0.077	13.568	0.000	0.812	0.659
Factor9	FP11	1.142	0.079	14.504	0.000	0.850	0.723
Factor9	FP12	1.119	0.074	15.138	0.000	0.875	0.766

Factor loadings

Factor	Items	Unstandardized factor loading (Coef.)	Standard error	z (CR value)	p	Standardized factor loading (Std. Estimate)	SMC
Factor9	FP2	1.041	0.086	12.042	0.000	0.744	0.553
Factor9	FP3	1.117	0.078	14.309	0.000	0.842	0.710
Factor9	FP4	1.049	0.084	12.433	0.000	0.762	0.580
Factor9	FP5	1.024	0.080	12.866	0.000	0.781	0.610
Factor9	FP6	1.018	0.089	11.428	0.000	0.715	0.511
Factor9	FP7	1.006	0.085	11.817	0.000	0.733	0.538
Factor9	FP8	1.080	0.077	13.959	0.000	0.828	0.686
Factor9	FP9	1.062	0.080	13.232	0.000	0.797	0.636
Factor10	LAIK1	1.000	-	-	-	0.856	0.733
Factor10	LAIK2	1.171	0.091	12.832	0.000	0.846	0.716
Factor10	LAIK3	0.934	0.083	11.289	0.000	0.736	0.542

Note: ‘-’ indicates that this item is a reference item.

5.5 Measurement scale reliability

As discussed in chapter 5.3.4, the most common method to test scale reliability is to use Cronbach’s alpha (Taber, 2018; Cronbach, 1947). Thus, in order to measure the reliability of all scales with the updated constructs, their Cronbach's alphas are calculated again and displayed in Table 5.6.

Table 5.6: Cronbach’s alpha coefficients of all the constructs (final)

Constructs (number of items)	Cronbach α
EXPT (4)	0.821
EXPR (4)	0.838
DDC (3)	0.815

CP (5)	0.882
NP (3)	0.910
MP (3)	0.910
TAIC (18)	0.960
NAIC (16)	0.962
FP (12)	0.954
LAIK (3)	0.851

In general, after removing inappropriate items for EXPT, EXPR, DDC, CP, NAIC, and TAIC, Cronbach's alphas also changed accordingly. According to the standard, they still show good reliability as their alpha values are all above 0.8 (Cronbach, 1951), indicating that they all have very good internal consistency.

Previous research also points out the need to consider some potential problems that may be suggested by alpha values exceeding 0.95, such as whether there are redundant items (Diamantopoulos et al., 2012). However, it is also proved that when a construct has a large number of items, Cronbach's alpha may be relatively high (Hair et al., 2010). Since items under the same construct are elaborating on the same theme, a large number of items will lead to higher correlation or internal consistency. Therefore, although the alphas of TAIC, NAIC, and FP are greater than 0.95, given that they contain 18, 16, and 12 items respectively, high alpha values here are acceptable. The most important thing, and one that has been emphasized, is that the scales and items used in this study come from well-cited literature and research, which means they have been tested to be reliable in many existing studies. In conclusion, the reliability of the scale in this study meets the research requirements.

5.6 Measurement scale validity

Validity is used to indicate whether the design of scale and items is reasonable. Generally, validity can be divided into convergent validity and discriminant validity (Campbell and Fiske, 1959). Convergent validity means that the measurement items under the same construct are indeed aggregated under the factor, meaning that they have a high correlation. Discriminant validity means that those measurement items that should not fall under the same construct actually do not fall under the same factor, thus ensuring the discrimination of the scale (Campbell and Fiske, 1959). These two jointly verify the rationality/validity of the scale design.

Convergent validity is usually analysed using AVE (average variance extraction) and CR (combined reliability) (Shrestha, 2021). Following the CFA method, AVE and CR values can be calculated. Table 5.7 shows the calculation results for all factors/constructs.

Table 5.7: AVE and CR values of all factors

Factor	AVE	CR
EXPT	0.548	0.829
EXPR	0.587	0.849
DDC	0.634	0.836
CP	0.617	0.888
NP	0.773	0.911
MP	0.781	0.914
TAIC	0.570	0.959
NAIC	0.621	0.963
FP	0.635	0.954
LAIK	0.664	0.855

It can be known from Table 5.7 that the AVE values of all the 10 factors are greater than 0.5, and their CR values are all greater than 0.7, which means that the scale items analysed in this study have good convergent validity (Fornell and Larcker, 1981; Hair et al., 2010).

When it comes to testing discriminant validity, Pearson correlation analysis is usually adopted. Table 5.8 provides results of Pearson correlation and AVE values. In the table, numbers located in the diagonal line of the table are AVE, and the remaining values are correlation coefficients. The AVE value can represent the aggregation of factors. Based on the judgment principles

(Fornell and Larcker, 1981), if the factor aggregation is very strong (significantly stronger than the absolute value of the correlation coefficient with other factors), it can indicate good discriminant validity. In other words, if each factor's AVE value is greater than the absolute value of the correlation coefficient between this factor and other factors, and all factors show such a conclusion, then a good discriminant validity is established. Moreover, the HTMT (Heterotrait-monotrait ratio) method is used to further test discriminant validity. Research recommends there should not be any HTMT values larger than 0.85 (Wong, 2019). Table 5.8 shows that there is only one value slightly exceeding this cutoff. Considering sometimes a value lower than 0.9 can be accepted when the constructs are preset (Franke and Sarstedt, 2019), HTMT check also effectively illustrates that the factors have a good discriminant validity.

Table 5.8: Pearson correlation and AVE values

	EXPT	EXPR	DDC	CP	NP	MP	TAIC	NAIC	FP	LAIK
EXPT	0.741									
EXPR	0.651	0.766								
DDC	0.705	0.550	0.797							
CP	0.675	0.569	0.695	0.785						
NP	0.246	0.318	0.243	0.372	0.879					
MP	0.498	0.525	0.457	0.622	0.550	0.884				
TAIC	0.442	0.469	0.370	0.437	0.318	0.467	0.795			
NAIC	0.540	0.501	0.472	0.533	0.254	0.481	0.787	0.788		
FP	0.467	0.457	0.372	0.453	0.244	0.465	0.577	0.643	0.797	
LAIK	0.386	0.376	0.193	0.277	0.065	0.284	0.336	0.335	0.342	0.815

Note: Blue numbers are AVE values.

Table 5.9: HTMT results

	EXPT	EXPR	DDC	CP	NP	MP	TAIC	NAIC	FP	LAIK
EXPT	-									
EXPR	0.780	-								
DDC	0.861	0.665	-							

	EXPT	EXPR	DDC	CP	NP	MP	TAIC	NAIC	FP	LAIK
CP	0.793	0.662	0.818	-						
NP	0.282	0.363	0.283	0.417	-					
MP	0.573	0.597	0.534	0.697	0.604	-				
TAIC	0.498	0.523	0.424	0.481	0.339	0.499	-			
NAIC	0.609	0.555	0.541	0.582	0.271	0.511	0.813	-		
FP	0.529	0.508	0.426	0.497	0.261	0.498	0.605	0.671	-	
LAIK	0.459	0.444	0.240	0.323	0.075	0.322	0.377	0.370	0.382	-

5.7 Descriptive statistics

Table 5.10 shows descriptive statistics about each construct of the scale. A consistent measurement method was used for each construct, namely a 7-point Likert scale ranging from 1 for “strongly disagree” to 7 for “strongly agree”. Statistics indicate that respondents show positive responses to all the constructs. Except for LAIK, the mean values of the other constructs are above 5, which means that their average response levels are higher than "somewhat agree". The standard deviation (SD) less than 2 means that the data is normally distributed (Field, 2013), which is consistent with the results of the normality test. For the sample firms, their perception of exploration and exploitation is similar (the average values are close), indicating that they are not obviously more inclined to adopt exploration or exploitation strategies. The distribution of leaders' AI knowledge level is relatively more uneven (SD value greater than 1), meaning that the difference in this item between samples is slightly larger than other items. Among the three types of institutional pressures, the whole sample has the highest perception of coercive pressure, with its average level even very close to 6 ("agree"). Firms also do not show significant differences in their levels of NAIC and TAIC. In addition, the overall DDC of the sample firms is relatively great, and perception is higher than the "agree" level.

Table 5.11 further provides descriptive statistics for specific items under each construct. It also illustrates that there are no missing values in the data used for analysis.

Table 5.10: Descriptive statistics for constructs

Construct	N	Mean	SD
EXPR	206	5.549	0.943
EXPT	206	5.765	0.759
LAIK	206	4.744	1.374
CP	206	5.925	0.807
NP	206	5.413	1.183
MP	206	5.615	0.952
NAIC	206	5.284	0.960
TAIC	206	5.068	1.044
FP	206	5.329	0.861
DDC	206	6.015	0.751

Table 5.11: Descriptive analysis for items under each construct

Construct	Item	Valid N	Min	Max	Mean	SD
EXPT	EXPT1	206	2	7	5.607	0.971
	EXPT2	206	2	7	5.704	1.024
	EXPT4	206	2	7	5.830	0.913
	EXPT5	206	3	7	5.917	0.843
EXPR	EXPR1	206	2	7	5.597	1.121
	EXPR2	206	2	7	5.597	1.112
	EXPR3	206	2	7	5.646	1.071
	EXPR4	206	1	7	5.354	1.255
LAIK	LAIK1	206	1	7	5.063	1.432
	LAIK2	206	1	7	4.413	1.696
	LAIK3	206	1	7	4.757	1.555
DDC	DDC1	206	2	7	6.117	0.930
	DDC4	206	2	7	5.927	0.844
	DDC5	206	3	7	6.000	0.861
CP	CP1	206	2	7	6.015	0.970
	CP2	206	2	7	5.864	1.022

Construct	Item	Valid N	Min	Max	Mean	SD
	CP3	206	2	7	5.971	0.982
	CP4	206	3	7	5.859	0.980
	CP8	206	2	7	5.917	0.941
NP	NP1	206	1	7	5.383	1.300
	NP2	206	1	7	5.553	1.282
	NP3	206	1	7	5.301	1.275
MP	MP1	206	2	7	5.534	1.111
	MP2	206	3	7	5.621	0.989
	MP3	206	2	7	5.689	0.998
TAIC	DATA4	206	1	7	5.049	1.298
	DATA5	206	1	7	5.170	1.275
	DATA6	206	1	7	5.131	1.252
	TECH1	206	1	7	5.252	1.259
	TECH2	206	1	7	5.267	1.206
	TECH4	206	1	7	5.102	1.349
	TECH5	206	1	7	5.053	1.415
	TECH7	206	1	7	4.976	1.436
	BR2	206	1	7	4.917	1.437
	BR3	206	1	7	4.903	1.369
	TS1	206	1	7	5.369	1.189
	TS2	206	1	7	5.383	1.141
	TS3	206	1	7	4.917	1.386
	TS4	206	1	7	5.058	1.360
	TS5	206	1	7	5.083	1.368
	TS6	206	1	7	5.005	1.419
	TS7	206	1	7	4.728	1.606
	TS8	206	1	7	4.854	1.542
NAIC	BS1	206	1	7	5.049	1.343
	BS2	206	1	7	5.218	1.275
	BS3	206	1	7	5.252	1.183
	BS4	206	1	7	5.068	1.392
	BS5	206	1	7	5.053	1.337

Construct	Item	Valid N	Min	Max	Mean	SD
	BS6	206	1	7	5.248	1.230
	BS7	206	2	7	5.330	1.225
	BS8	206	1	7	5.194	1.318
	BS9	206	1	7	5.417	1.190
	OCC1	206	2	7	5.184	1.048
	OCC2	206	2	7	5.408	1.054
	OCC3	206	2	7	5.539	1.076
	OCC4	206	2	7	5.534	1.006
	OCC5	206	2	7	5.417	1.087
	OCC6	206	2	7	5.432	1.110
	RP2	206	1	7	5.199	1.239
FP	FP1	206	2	7	5.500	0.986
	FP2	206	2	7	5.291	1.110
	FP3	206	2	7	5.383	1.052
	FP4	206	2	7	5.126	1.093
	FP5	206	2	7	5.510	1.039
	FP6	206	1	7	4.811	1.130
	FP7	206	1	7	5.252	1.088
	FP8	206	2	7	5.403	1.035
	FP9	206	3	7	5.388	1.057
	FP10	206	3	7	5.485	1.020
	FP11	206	2	7	5.350	1.066
	FP12	206	3	7	5.447	1.014

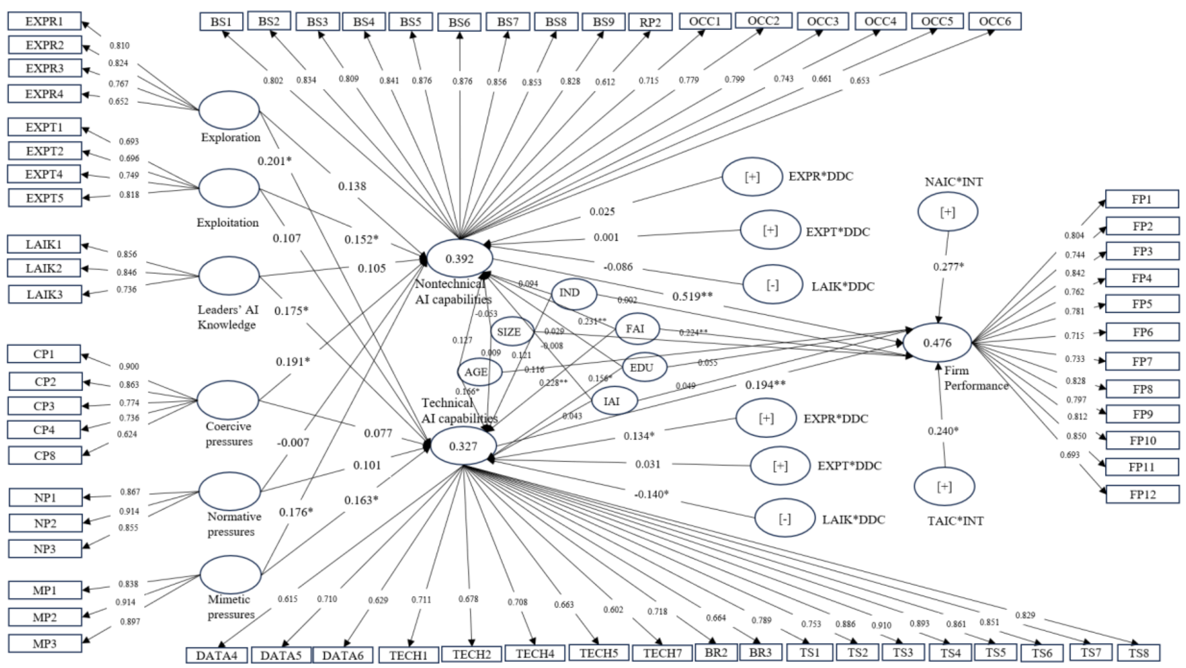
5.8 Hypothesis testing

According to the above demonstration, the variables and data involved in this study have good validity and reliability. Based on this, the researcher uses structural equation modelling (SEM) to test the conceptual model and examine all the hypotheses (relationships between variables) proposed in chapter 3.4.

5.8.1 Structural equation modelling

Based on the proposed conceptual model and construct settings, the researcher runs SEM analysis incorporating all control variables. Among the control variables, firm's AI experiences (FAI) shows the most importance as it has very significant effects on NAIC, TAIC, and performance, while firm age (AGE) and leader's education background (EDU) also significantly control TAIC. The other control variables do not show significant effects on the dependent variables. Figure 5.1 illustrates the SEM results. The ellipses in the figure represent variables, and the rectangles represent items. The value between each variable and item is the factor loading calculated in chapter 5.4.2. The arrow direction and value between different variables represent the direction and degree of the respective effect/relationship. The value marked with asterisk in a relationship means the corresponding effect is significant. The number in the ellipse means the fitting degree or interpretation strength of the model (R^2). The results of SEM will be further explained in detail in the following sections.

Figure 5.1: SEM results of conceptual model



5.8.2 Direct effects

Table 5.12 shows the direct effects between the variables. The p-value is a statistical measure used to test whether a hypothesis is true. According to statistical rules (Fisher, 1970), when the p value is <0.05, it means the relationship between variables is significant, and the corresponding hypothesis is supported. Otherwise, it is not supported. Especially when the p-value is <0.01, the relationship is considered highly significant. Based on this rule, the direct effects in the hypotheses of this study are first examined. Moreover, the β value refers to the path coefficient, that is, the effect weight. R^2 means the fitting degree or interpretation strength of the model, which is usually between 0 and 1. It is generally acknowledged that the closer R^2 is to 1, the better the model fits the data. However, in social science research, if there is a significant relationship between some or most variables, then an R^2 between 0.1-0.5 is acceptable (Ozili, 2023).

Table 5.12: Results of direct effects

Effect relationship			*p*	β	Results
NAIC					R^2=0.392
EXPR	→	NAIC	0.073	0.138	Not supported
EXPT	→	NAIC	0.016*	0.201	Supported
LAIK	→	NAIC	0.076	0.107	Not supported
CP	→	NAIC	0.022*	0.191	Supported
NP	→	NAIC	0.914	-0.007	Not supported
MP	→	NAIC	0.042*	0.163	Supported
TAIC					R^2=0.327
EXPT	→	TAIC	0.233	0.105	Not supported
EXPR	→	TAIC	0.031*	0.175	Supported
LAIK	→	TAIC	0.017*	0.152	Supported
CP	→	TAIC	0.379	0.077	Not supported
NP	→	TAIC	0.145	0.101	Not supported
MP	→	TAIC	0.036*	0.176	Supported
FP					R^2=0.476

Effect relationship			p	β	Results
NAIC					R^2=0.392
NAIC	→	FP	0.000**	0.519	Supported
TAIC	→	FP	0.001**	0.194	Supported

Firstly, among all variables that have a direct impact on the variable NAIC, exploitation (p=0.016, β=0.201), coercive pressure (p=0.022, β=0.191), and mimetic pressure (p=0.42, β=0.163) show significant effects (p<0.05). Therefore, hypotheses **H1b, H1d, and H1f are supported**. On The other hand, exploration (p=0.073), leaders' AI knowledge (p=0.076), and normal pressure (p=0.914) have no significant impact on NAIC. Hypotheses **H1a, H1c, H1e are not supported**.

Second, among all variables that have a direct impact on the variable TAIC. The impact of exploration (p=0.031, β=0.175), leaders' AI knowledge (p=0.017, β=0.152), and mimetic pressure (p=0.036, β=0.176) on TAIC is significant (p<0.05). Therefore, hypotheses **H2a, H2c, H2f are supported**. Exploitation (p=0.233), coercive pressure (p=0.379), and normal pressure (p=0.145) have no significant impact on NAIC. Hypotheses **H2b, H2d, H5e are not supported**.

Finally, NAIC (p=0.000, β=0.519) and TAIC (p=0.001, β=0.194) are both proved to have a significant direct effect (p<0.05) on firm performance. Thus, hypotheses **H3a and H3b are supported**.

5.8.3 Moderating effects

Table 5.13 shows the results of testing data-driven culture (DDC) as moderator in the relationships between NAIC and TAIC and their firm-level antecedents. The moderating effect of DDC is significant (p<0.05) on relationships between exploration and TAIC (p=0.034, β=0.134) as well as LAIK (leaders' AI knowledge) and TAIC (p=0.035, β=-0.140). So hypotheses **H4d and H4f are supported**. The other p values indicate that DDC as moderator shows no significance on the other relationships, which means **H4a, H4b, H4c, H4e are not supported**. Figure 5.2 shows that a high level of DDC would enhance the effect of exploration on TAIC, while Figure 5.3 shows DDC negatively moderates the effect of LAIK on TAIC, which means a high level of DDC would attenuate this effect.

Table 5.13: DDC as moderator

Effect of DDC on			*p*	β	R^2	Results
EXPR	→	NAIC	0.684	0.025		Not supported
EXPT	→	NAIC	0.987	0.001		Not supported
LAIK	→	NAIC	0.183	-0.086		Not supported
EXPR	→	TAIC	0.034*	0.134	0.349	Supported
EXPT	→	TAIC	0.647	0.031		Not supported
LAIK	→	TAIC	0.035*	-0.140	0.281	Supported

Figure 5.2: DDC moderating EXPR and TAIC

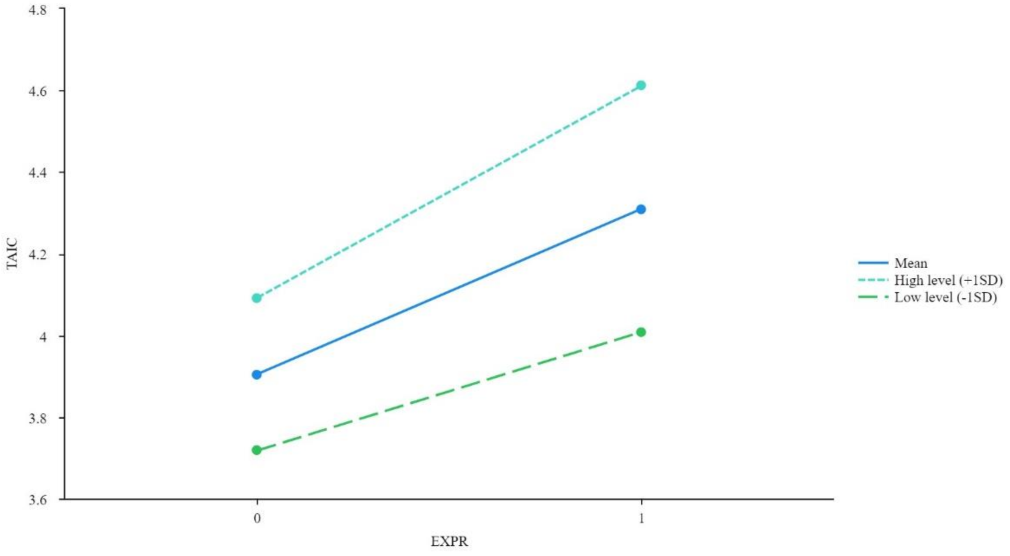


Figure 5.3: DDC moderating LAIK and TAIC

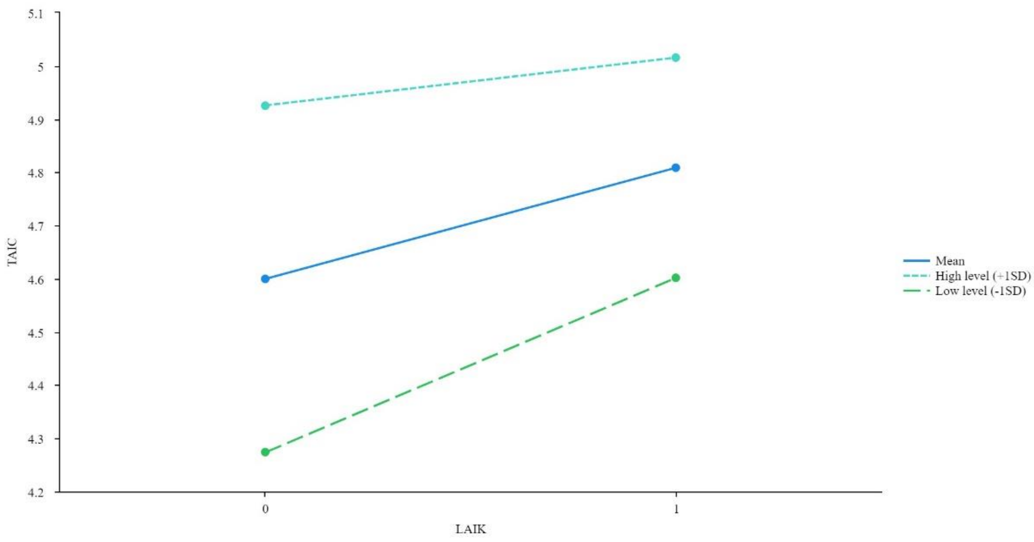


Table 5.14 shows the results of testing firm's international presence (INT) as moderator in the relationships between NAIC and TAIC and firm performance. It needs to be noted that INT does not use scale items to measure. It is a single choice question in the questionnaire for respondents to answer what kinds of international business activities their firms run. Therefore, here it is converted into a dummy variable. The first three options of the original question (export, import, or both) uniformly represent that the firm conducts international business (1), while the last option (no) indicates that the firm has no international business (0), in order to test the moderating effect of INT.

Table 5.14: INT as moderator

Effect of INT on	*p*	β	R^2	Results
NAIC → FP	0.018*	0.277	0.444	Supported
TAIC → FP	0.043*	0.240	0.361	Supported

Unlike DDC, the results in the table do not reflect the moderating effect of varying degrees of INT. Because INT is set to categorical data rather than quantitative data. In fact, it means, compared to the case where the firm has no international business (0), whether the existence of international business (1) has a significant impact on the effect of NAIC/TAIC on firm performance. Therefore, the results indicate that in comparison with the absence of international operations, the presence of international business operation significantly influences the effects of NAIC and TAIC on firm performance. So hypotheses **H5a and H5b are supported**. Figure 5.4 and 5.5 further illustrate the positive effects of this moderation. When the firm is involved in international business (1), the positive effects of NAIC and TAIC on performance will be more obvious.

Figure 5.4: INT as moderator between NAIC and FP

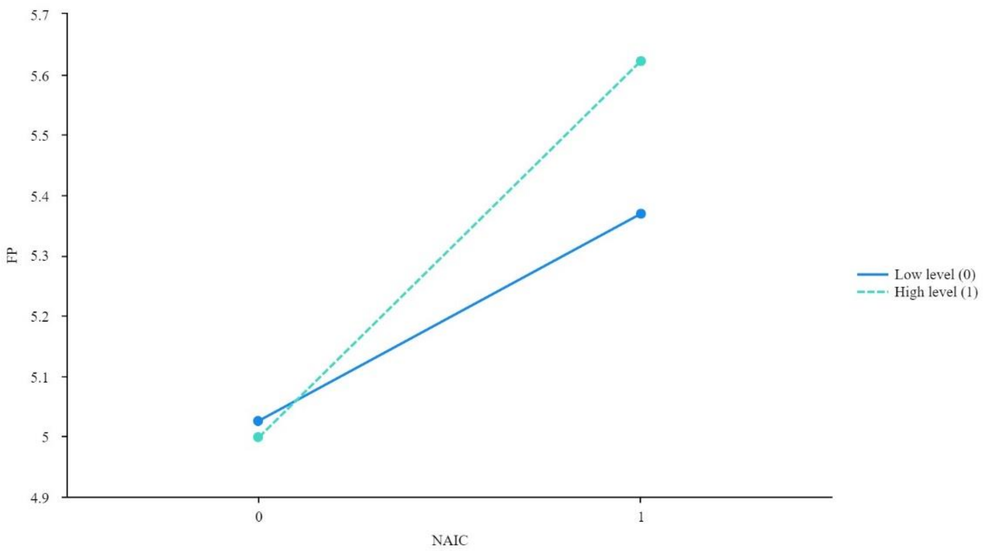
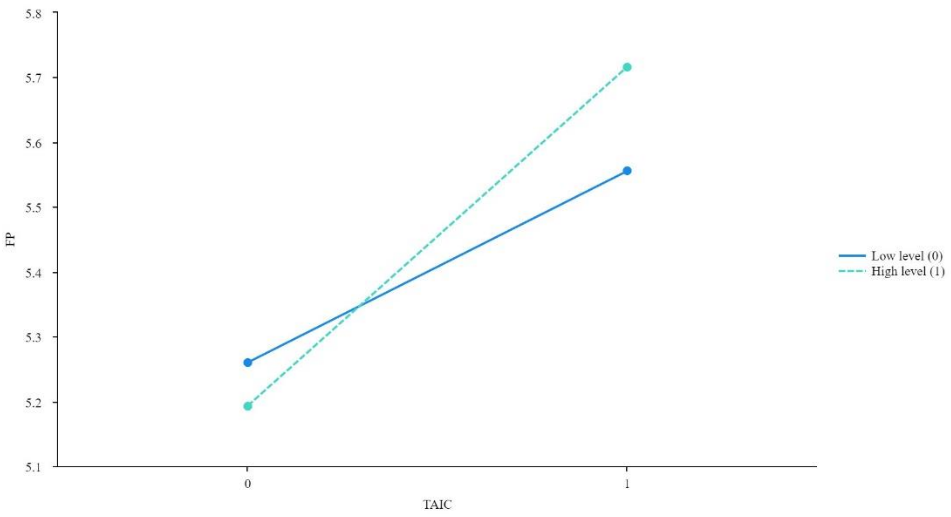


Figure 5.5: INT as moderator between TAIC and FP



5.8.4 Mediating effects

The present research mainly studies the impact of various antecedents on AIC and its impact on firm performance, and no hypothesis is made about the mediating effects of NAIC or TAIC. However, as the core study objects, it is meaningful to analyse the mediating roles of the two to gain more insights from the results. The results of the mediating effect obtained using Bootstrap test method in SEM are shown in Table 5.15. It is found that NAIC can play a fully mediating role in the relationship between exploration and firm performance as well as coercive pressure and firm performance, while TAIC only plays a fully mediating role in the relationship between exploration and firm performance.

Table 5.15: Mediating effects of NAIC and TAIC

Effect relationship	β	p	Conclusion
EXPR=>NAIC=>FP	0.062	0.175	No mediation
EXPT=>NAIC=>FP	0.125	0.034*	**Full mediation**
LAIK=>NAIC=>FP	0.029	0.431	No mediation
CP=>NAIC=>FP	0.090	0.040*	**Full mediation**

Effect relationship	β	p	Conclusion
NP=>NAIC=>FP	-0.000	0.994	No mediation
MP=>NAIC=>FP	0.055	0.236	No mediation
EXPR=>TAIC=>FP	0.068	0.052*	**Full mediation**
EXPT=>TAIC=>FP	0.048	0.282	No mediation
LAIK=>TAIC=>FP	0.027	0.431	No mediation
CP=>TAIC=>FP	0.024	0.505	No mediation
NP=>TAIC=>FP	0.027	0.467	No mediation
MP=>TAIC=>FP	0.046	0.184	No mediation

5.8.5 Summary of the research hypotheses testing results

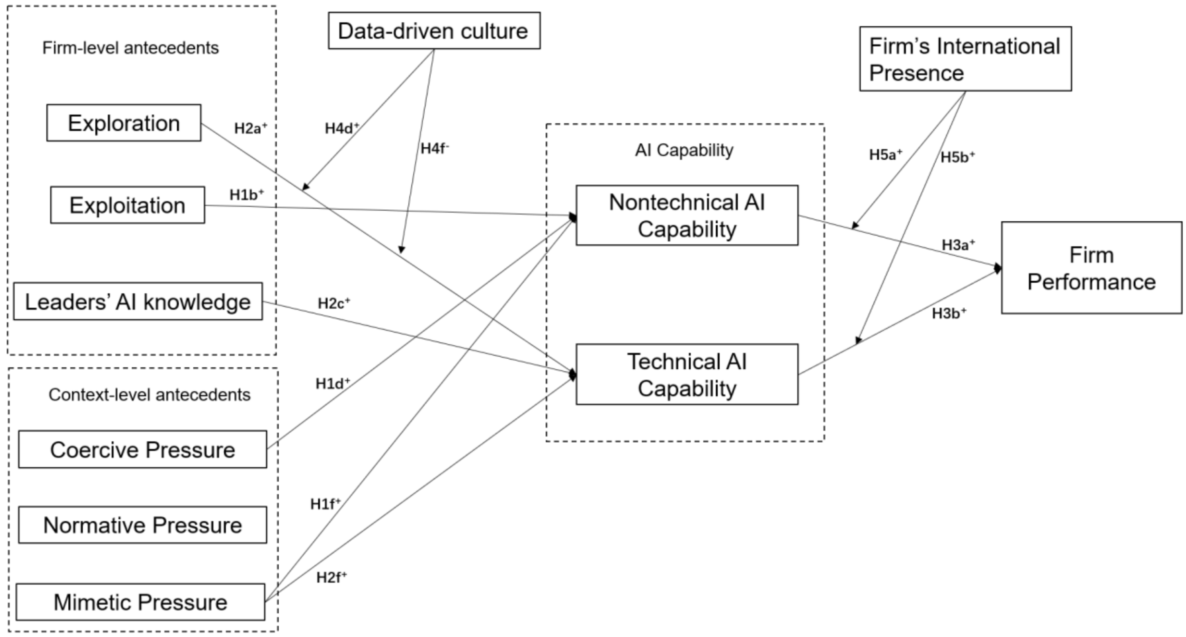
To clearly summarize the results of SEM analysis, Table 5.16 puts together all the hypotheses and their corresponding results (supported or not supported). Figure 5.6 more intuitively shows the conceptual model that only keeps the verified and supported hypotheses to illustrate the significant relationships between variables.

Table 5.16: Summary of research hypotheses and results

	Hypotheses	Results
H1a	Firm's exploration is positively related to its NAIC.	Not supported
H1b	Firm's exploitation is positively related to its NAIC.	Supported
H1c	Leaders' AI knowledge level has a positive relationship with NAIC.	Not supported
H1d	There is a positive relationship between coercive pressures and firm's NAIC.	Supported
H1e	There is a positive relationship between normative pressures and firm's NAIC.	Not supported

H1f	There is a positive relationship between mimetic pressures and firm's TAIC.	Supported
H2a	Firm's exploration is positively related to its TAIC.	Supported
H2b	Firm's exploitation is positively related to its TAIC.	Not supported
H2c	Leaders' AI knowledge level has a positive relationship with TAIC.	Supported
H2d	here is a positive relationship between coercive pressures and firm's TAIC.	Not supported
H2e	There is a positive relationship between normative pressures and firm's TAIC.	Not supported
H2f	There is a positive relationship between mimetic pressures and firm's TAIC.	Supported
H3a	Firm's NAIC has a positive effect on its performance.	Supported
H3b	Firm's TAIC has a positive effect on its performance.	Supported
H4a	Data-driven culture moderates the relationship between firm's exploration and NAIC.	Not supported
H4b	Data-driven culture moderates the relationship between firm's exploitation and NAIC.	Not supported
H4c	Data-driven culture moderates the relationship between leaders' AI knowledge level and NAIC.	Not supported
H4d	Data-driven culture moderates the relationship between firm's exploration and TAIC.	Supported
H4e	Data-driven culture moderates the relationship between firm's exploitation and TAIC.	Not supported
H4f	Data-driven culture moderates the relationship between leaders' AI knowledge level and TAIC.	Supported
H5a	Firm's international presence enhances the relationship between its NAIC and performance.	Supported
H5b	Firm's international presence enhances the relationship between its TAIC and performance.	Supported

Figure 5.6: Conceptual model with significant relationships only



5.9 Chapter summary

This chapter conducted detailed and comprehensive analysis of the data collected from the 206 sample firms. First, the characteristic information of the sample firms and respondents was collected based on the responses to the questionnaire. Secondly, the data was screened and no missing values or outliers were found. The data overall conforms to the requirements of normal distribution. Initial reliability tests indicate that the scale items require further refinement. Therefore, CFA was performed, and internally inconsistent or redundant items in the scale were removed based on the CFA results. Then, by calculating Cronbach's alpha, AVE, CR, HTMT and other values of all variable constructs, it was verified that the modified scale used in this study has good reliability, convergent validity, and discriminant validity. Next, descriptive statistical analysis was conducted on the data, and the overall performance of the sample on different measurement items was observed. Finally, SEM analysis was done on the hypotheses and conceptual model of this study using the screened data and scales, and a conclusion was obtained as to whether all hypotheses were supported. The empirical testing results in this chapter lay the foundation for the following discussion.

Chapter 6: Discussion

6.1 Introduction

Based on the data analysis results in chapter 5, this chapter will provide a detailed discussion of the findings reflected from the results. First, according to the research objectives, it will discuss the findings verified by the empirical test, including firm-level and context-level antecedents for both NAIC and TAIC, the impact of AIC on firm performance, and the impact of moderator variables (data-driven culture and firm international performance) on the relationship as well as potential reasons for the moderating effect. Then the theoretical contribution of this study to RBV, institutional theory and AI literature will be demonstrated, especially how the establishment of the concepts of NAIC and TAIC promotes the development of related theories. Finally, the implications of this study for management practices and policy makers will be talked through.

6.2 Overview of Research Findings

6.2.1 Antecedents for NAIC

Taking into account the joint effects of internal exploration and exploitation strategies, leaders' AI knowledge level, and external institutional pressures, it was found that exploitation, coercive pressures, and mimetic pressures have a significant impact on corporate NAIC. This result was explained to a degree of 39.2% (R^2).

Firm-level antecedent for NAIC: exploitation

NAIC represents a firm's ability to accumulate and utilize AI-related nontechnical resources which will not directly help improve the level of the firm's AI techniques. From the perspective of firm strategies, exploration and exploitation are the two main ways to apply digital technologies (Jafari-Sadeghi et al., 2021). The results of this study find that only exploiting existing resources can improve a firm's NAIC, such as business skills and organizational change capacity. For example, by utilizing and upgrading already mature AI techniques and knowledge, firms can understand market trends, competitors, and customer needs faster and better, providing support for formulating more appropriate business strategies (Caputo et al., 2022). On the basis of existing techniques and knowledge, firms can quickly understand customer preferences and provide customized products and services (Huang et al., 2017; Tao et al., 2018). Firms can also further implement personalized customer relationship management, thereby improving customer satisfaction and loyalty (Chatterjee et al., 2021). Meanwhile, using existing resources can help firms discover new business and innovation opportunities. Existing AI techniques can enable firms to efficiently mine information in data, discover new market demands, develop new products and services, and explore new business models, thus improving the business skills (Garbuio and Lin, 2019). In addition, learning from existing knowledge and experience can help firms successfully conduct change management and organizational learning. In particular, they can predict, identify, and manage risks and challenges in the change process based on existing knowledge and experience (Hoang and Rothaermel., 2010). Learning from past experiences and adjusting strategies and execution plans in a timely manner can maintain the organization's stability in the process of intelligent transformation.

Context-level antecedents for NAIC: coercive and mimetic pressures

Among the three types of institutional pressures, coercive pressure and mimetic pressure have been proven to be effective for NAIC. Among them, the impact of coercive pressure is slightly greater. Coercive pressure mainly comes from government laws, regulations and policies (DiMaggio and Powell, 1983). The implementation of these laws and regulations force firms to pay more attention to legality. This helps firms accumulate nontechnical AI-related resources, such as establishing a sound internal compliance system and strengthening the identification and management of legal risks. These resources can enhance a firm's business skills and risk proclivity. Laws and regulations also impose a series of requirements on data management and privacy protection (Bag et al., 2021). This encourages firms to strengthen data management and protection, improve their data security awareness and capabilities, and establish complete data protection mechanisms to respond to legal and regulatory requirements. In addition, government restrictions and regulations have promoted the standardized development of related industries and promoted benign competition within the industry (Beardsley and Farrell, 2005). While complying with laws and regulations, firms may actively participate in the formulation and improvement of industry norms, thereby helping organizations adapt to changes in many aspects. On the other hand, in China, the government will also introduce some positive policies, such as financial support, tax cuts, or other economic incentives to encourage firms' AI deployment and reduce their financial burden (Cheng et al., 2020). Although this cannot directly contribute to the innovation of AI techniques, it can reduce the risk of firms falling into commercial difficulties to a certain extent.

Facing the others' success in AI applications, firms may feel pressure to mimic and learn from their peers' experiences and best practices (Lin et al., 2018). By studying the successful cases, although they may not necessarily have access to secrets such as the core techniques used by others, firms can still generally understand the application methods and effects of AI techniques in different fields, thus better adjusting their own strategies and business model. When faced with competitors' success, firms will also strengthen their nontechnical resources such as market sensitivity and competitive awareness (Dubey et al., 2019b). In other words, they will pay more attention to market dynamics and competitors' actions, and adjust their strategies and actions timely to remain competitive (Srinivasan and Swink, 2018). This requires firms to have the ability to respond quickly and adjust flexibly. Mimetic pressure can also prompt them to continuously promote organizational innovation and change, to respond to market changes and challenges from competitors. Firms may promote the deployment of AI techniques within the organization to continuously improve business processes and efficiency. This ongoing process of innovation and change helps improve business skills and organizational change capacity.

The other potential antecedents

It is also necessary to discuss why other variables proposed by the research hypotheses do not play a significant role in firm NAIC.

First, exploration involves learning and developing AI resources that are new to the organization. Although it is of great significance in terms of technical innovation and development (this will be discussed in the next section), it cannot directly help with firms' NAIC. Brand-new techniques and knowledge have not been practically verified, and their commercial applications and effects are still uncertain (Kapoor and Lee, 2013). Therefore, although exploration may provide firms with new technical resources and knowledge reserves, it is uncertain whether they can be directly transformed into actual value that can be used in commercial activities. Moreover, the learning and development process of new techniques often requires significant time, human, and financial investment (Fountaine et al., 2019; Nwankpa and Datta, 2017). During the exploration process, firms may need to conduct long-term R&D activities to transform new AI techniques and knowledge into products or services, which may cause the obtained resources to be dispersed and delayed. Such exploration is fraught with risk and uncertainty (Kapoor and Lee, 2013). Therefore, during the exploration phase, firms need to take greater risks and may face the possibility of failure, which challenges the organization's change capacity and risk proclivity.

Secondly, leaders’ AI knowledge is mainly related to the technical aspect, while NAIC involves nontechnical capabilities such as organizational management, strategic planning, marketing, etc. Although leaders' AI (technical) knowledge can help firms understand and apply AI techniques to some extent, the improvement of NAIC requires more business insight, leadership, and strategic vision (Mikalef and Gupta, 2021). In addition, firms keep being affected by the external environment, including market demand, industry competition, policies and regulations (Dubey et al., 2020). Even if leaders have a rich understanding of AI techniques, if they cannot help the organizations effectively respond to the dynamic environment, it will be difficult to improve the firms’ business skills or complete the required organizational changes.

Finally, compared with coercive and mimetic pressures, normative pressure does not have a significant impact on firm NAIC. This has also been confirmed in previous studies on the relationship between institutional pressure and firms' use of new technologies (Krell et al., 2016; Lin et al., 2020; Lin et al., 2021). Considering China's special environment, the government often has greater influence on firms (Cheng et al., 2020). Meanwhile, competition drives firms to constantly mimic successful competitors. It is therefore understandable that the effect of normative pressure is less pronounced in comparison.

6.2.2 Antecedents for TAIC

When considering the combined effects of all antecedents, the significant impact of exploration, leaders’ AI knowledge, and mimetic pressures on TAIC was explained by 32.7% (R^2).

Firm-level antecedents for TAIC: exploration and leaders' AI knowledge

Exploration strategy drives firms to continuously research and try new AI techniques and solutions. Through exploration, firms can learn about emerging technical trends and adjust their own technical development direction timely. They will have the opportunity to further discover new algorithms or tools and directly promote the progress of their own AI techniques. Exploration activities also include the collection, organization, and analysis of new data resources, thereby helping firms better understand and utilize big data (Johnson et al., 2017). By accumulating more data resources and using advanced technical means to analyse the data, firms can optimise data usage and improve data-driven TAIC. Besides, organizations usually attract and cultivate talents with relevant AI expertise when conducting technical exploration (Jafari-Sadeghi et al., 2021). These talents, in turn, can help firms improve their technical capabilities. Exploration activities also encourage employees to develop innovative thinking and practices and promote an innovative cultural atmosphere within the organization (Jurado-Salgado et al., 2024), which helps with the continuous improvement of TAIC especially technical innovation.

Leaders with AI expertise understand the application scenarios and benefits of AI techniques and can rationally allocate resources including data, technology, and talent. Through leaders' decision-making, firms can more accurately invest in the appropriate resources required for AI techniques, improve efficiency of resource utilization, and achieve rapid improvement in technical capabilities (Pan et al., 2019; Singh and Hess, 2020). Leaders' AI knowledge is also a resource in itself (Mikalef and Gupta, 2021). It can stimulate a climate of learning and innovation within the organization. By sharing the latest AI knowledge and cases, leaders are able to inspire employees to explore learning and innovation in AI techniques. In addition, leaders' AI knowledge may help firms establish good strategic partnerships with external technique partners (Ettlie and Pavlou, 2006; Kilubi, 2016; Zhang et al., 2019). They can find suitable partners based on the firm's needs and development, and jointly carry out AI technique R&D and application to further enhance the firm's technical capabilities.

Context-level antecedent for TAIC: mimetic pressures

When firms are inspired by the successful application of AI techniques by other competitors, they will hope to be able to quickly learn and mimic these successful cases. This competition-oriented learning and mimicry helps firms quickly follow up and acquire the latest AI techniques (Wang et al., 2024). Moreover, firms hope to outperform their competitors through continuous improvement. This encourages them to accelerate technical iteration and innovation, constantly explore new AI application scenarios, and thus improve their own TAIC. Mimetic pressure may also prompt firms to strengthen organizational learning and personnel training for AI techniques (Dhamija and Bag, 2020). Firms may invest more resources in cultivating employees' AI technical skills and professional knowledge to cope with challenges from competitors. Furthermore, firms may also choose to cooperate with other companies to explore and apply AI techniques together. Therefore, the positive impact of mimetic pressure on corporate TAIC can be observed.

The other potential antecedents

In the proposed model and hypotheses, the effects of exploitation as well as coercive and normative pressures on TAIC are not verified. The reason is that exploitation strategy usually means that firms use existing resources or upgrade based on existing models, lacking the drive for innovation and change. While they can solve some common business problems by leveraging owned resources, technical innovation often requires the investment of more resources (such as time and funding). Additionally, exploitation may lead firms to be content to use existing technical solutions and knowledge to address business challenges, lacking learning about new techniques or ignoring the importance of exploration (Piao and Zajac, 2016).

From the perspective of coercive pressures, the supervision of laws mainly prompts firms to comply with regulations in data processing and privacy protection, but usually does not provide direct technical guidance and support, so it cannot directly improve the firm TAIC. On the other hand, out of considerations for regulatory compliance requirements, firms may tend to be cautious and conservative, unwilling to try new techniques which may cause legal risks (Gu and Xie, 2022). Similar to coercive pressures, normative pressures tend to focus on compliance and social responsibility of corporate behaviour rather than technical innovation and progress.

Normative pressure may also make firms conservative or even lazy. Under such pressure, firms may tend to follow existing norms and expectations rather than proactively explore (Durand et al., 2019), causing stagnation in their technical levels.

6.2.3 Impact of AIC on firm performance

The positive effects of NAIC and TAIC on firm performance is very significant ($p<0.01$), which can be explained to a degree of 47.6% (R^2).

A high level of NAIC means that firms can better understand and apply nontechnical resources to solve business problems and integrate AI techniques into strategies and decision-making. Specifically, NAIC helps firms understand market demands, competitive landscape, and their own competitive advantages, thereby formulating more effective business strategies. By analysing data such as supplier and customer behaviour, they can better position their products/services and develop new ones to increase market share and profitability (Olabode et al., 2022). Meanwhile, the improvement of organizational change capacity enables firms to flexibly respond to changes in the external environment and achieve sustainable development through innovation (Mikalef and Gupta, 2021). In the face of volatility in the market, technical advances, and competitive pressures, firms need to continuously adjust and improve their organizational structures, processes, and cultures to adapt to new needs and challenges (Bustinza et al., 2015). Firms with good NAIC can adjust strategic directions more quickly and promote innovation and change in business models (Jorzik et al., 2023; Sjödin et al., 2021).

The role of TAIC in facilitating firm performance can also be easily understood. Data resources are the core of AI technique (Ransbotham et al., 2018). Data with high quality and diversity can provide firms with in-depth insights and understanding, allowing them to make more informed data-driven decisions (Zhang et al., 2021). AI techniques can help organizations achieve intelligent automation with improved work and production efficiency. With more advanced technical infrastructure, firms can automate tedious tasks and processes, reducing labour costs while improving efficiency. More advanced AI techniques can also help develop innovative products and services, improving firms' competitiveness and market position. Because techniques such as big data analysis, machine learning, and natural language processing can enable firms to identify market needs and potential opportunities (Mikalef et al., 2019b). In addition, the AI technical application requires the support and cooperation of talents with relevant technical skills (Wilson et al., 2017). Through training and recruiting such talents, firms can improve employees' AI technical level and application capabilities, stimulate their innovation potential and teamwork spirit, and promote innovation and development of the whole firm.

Another more meaningful finding is that compared to TAIC, NAIC actually has a more significant effect on improving firm performance. First of all, NAIC focuses more on strategic planning and the realization of business goals. Business skills enable firms to better understand the market and thereby develop strategic solutions that are more in line with market needs and the competitive environment (Moonen et al., 2019). Organizational change capacity makes firms able to effectively respond to internal and external changes and achieve sustained development through innovation (Besson and Rowe, 2012; Orlikowski, 1996). These NAICs together encourage firms to seize opportunities more accurately, thereby improving performance. Secondly, NAIC helps transform techniques into commercial competitiveness to some extent. Although TAIC directly promotes the advancement of AI techniques in firms, how to combine these techniques with business goals and organizational strategies to maximize their commercial value requires the promotion of NAIC. NAIC involves the ability to transform technical capabilities into business value. In addition, NAIC helps firms evaluate and improve their performance. Although AI techniques can also help organizations use big data analytics and other methods to efficiently and accurately understand their own performance (Hsu et al., 2022), identifying improvement opportunities and potential problems requires more assistance from business skills. Even if advanced AI techniques can predict performance changes and even provide corresponding suggestions (Chaudhuri et al., 2022), current research shows that a considerable number of managers will still prefer to rely on their own knowledge and experience judgment to make decisions related to performance improvement (Haesevoets et al., 2021). Finally, firms' rapid adjustments to strategic directions and organizational structures can promote the implementation and promotion of AI initiatives (Fountaine et al., 2019), which also improve firm performance levels and maintain firms' competitive advantages.

Mediating effects

The analysis of the mediating role of AIC also shows that NAIC can transmit the impact of exploitation on performance. In other words, NAIC can transform firms' exploitation of existing AI-related resources into actual performance. For example, when firms can accurately understand market trends and formulate appropriate marketing strategies, existing AI resources can be more effectively utilized to improve performance (Wu and Monfort, 2023). If firms can also quickly adjust their organizational structures and processes and improve employees' adaptability, they can more flexibly upgrade the existing AI resources to improve performance (Fountaine et al., 2019).

NAIC also explains the relationship between coercive pressure and firm performance. For example, business skills involve understanding of legal policy standards and coping strategies (Chaudhary, 2020). When regulatory pressure becomes greater, NAIC can help firms understand the impact of laws and regulations on technical development and market competition, so as to formulate corresponding plans and strategies to reduce legal risks and improve firm performance (Dvorsky et al., 2021). Meanwhile, quickly optimising organizational processes and improving employees' legal awareness can also help firms better respond to changes in laws and regulations, thereby improving firm performance.

TAIC represents a firm's ability to acquire, apply, and develop AI technical resources, and it can convey the impact of firm exploration on performance. Specifically, if firms increase their investment in AI resource exploration, they may acquire advanced data analysis tools and algorithms as well as high-level AI technical teams and technical architecture (Johnson, P.C. et al., 2022). These, in turn, enhance the ability to explore innovative AI techniques (Jafari-Sadeghi et al., 2021), make reasonable decisions, and further improve firm efficiency through technical progress, thus improving the performance.

6.2.4 Role of moderators

This study examines the moderating effects of two variables in different relationships. Among them, data-driven culture can positively moderate the relationship between exploration and TAIC, while negatively moderating the relationship between LAIK and TAIC. The explanation rates (R^2) of these two moderating effects in this model are 34.9% and 28.1% respectively. Firm international presence also has a significant moderating effect on NAIC as well as TAIC and firm performance. The explanation rates (R^2) are 44.4% (NAIC) and 36.1% (TAIC).

Data-driven culture as moderator

First, DDC emphasizes the importance of data. This culture treats data as a resource and encourages employees to proactively explore and utilize new data to support decision-making and innovation (Ross et al., 2013; McAfee and Brynjolfsson, 2012). Secondly, DDC focuses on the quality and effective use of data (Anderson, 2015). This requires firms to adopt advanced and appropriate technical means to analyse and apply data. Through this culture, firms are more inclined to invest in exploring high technology and infrastructure to support data analysis and other AI applications. The exploration of these technical resources will then help improve TAIC. In addition, DDC advocates data sharing, team collaboration, and continuous learning (Anderson, 2015; Berntsson Svensson and Taghavianfar, 2020). Under the influence of this culture, employees are willing to share data, technology, and practical experience. Through team efforts and learning, firms can explore AI resources more effectively and improve TAIC. Finally, DDC means paying attention to employees' data awareness and skills (Yu et al., 2021). Firms will invest more resources in training employees to develop their data analysis skills. Employees have more opportunities to receive professional training and enhance their technical skills, thus strengthening the overall firm TAIC. Therefore, DDC positively moderates the relationship between exploration and TAIC.

On the other hand, a very interesting phenomenon is that the higher level of DDC weakens the effect of LAIK on TAIC. In high-level DDC, decisions are often based on large amounts of data analysis and statistical results. In this case, leaders' AI knowledge may be marginalized as their decision-making power and influence may be replaced by results based more on data analysis. In other words, leaders' understanding and expertise in AI technique may be overlooked, resulting in its reduced influence on TAIC. This phenomenon has not been well studied in the existing literature. Another possible reason is that leaders may have a tendency to be overconfident because of their high level of AI expertise, or to overly trust their own judgment and decision-making (Russo and Schoemaker, 1992). This tendency can lead leaders to overinterpret data to fit their own opinions and judgments. They may even selectively adopt data and ignore the data that contradicts their own views, thus making biased and inaccurate decisions (Cohee and Barnhart, 2023; Kunz and Sonnenholzner, 2023). This kind of overconfidence is obviously contrary to the philosophy of DDC. Therefore, these two reasons may cause DDC to negatively moderate the relationship between LAIK and TAIC.

Firm international presence as moderator

The interplay between firm internationalization, digitalization, and performance has been examined in previous research. For example, Denicolai et al. (2021) study the positive impact of AI readiness on corporate export intensity. Cheng et al., (2020) investigate how business intelligence adoption accelerates firm internationalization speed by enhancing organizational agility. In particular, the research by Bhandari et al. (2023) supports the positive moderating effect of degree of outward internationalization on the relationship between firm digitalization and performance. The focus of this study is whether a firm's international presence moderates the relationship between AIC and performance. As a categorical variable, it does not reflect the degree of internationalization (such as speed and scale), but the moderating difference in the impact of whether the firm conducts international business on AIC. This study proves that compared with its absence, the presence of firm international business activities will enhance the impact of AIC on firm performance.

Compared to focusing only on local business, entering the international market can provide firms with broader business opportunities and market space, thereby increasing the sales volume and revenue (Arte and Larimo, 2021). Having good NAIC means that firms can use AI techniques to better understand the market needs of different countries and regions, formulate more effective international marketing strategies, and gain a higher share in the international market (Pereira et al., 2022b). Besides, the development of international business means that firms will face a more intense competitive environment (Hill, 2008). Excellent business skills and organizational change capacity also enable firms to better respond to competitive challenges (Parthasarthy and Sethi, 1992). International activities require excellent talent skills and management capabilities as well to cope with diversified market environments and cultural differences (Kabwe and Okorie, 2019). When handling international business, firms need to attract, cultivate, and manage talents with international vision and cross-cultural communication skills, and to establish efficient international teams and partnerships. This is also a reflection or result of the improvement of NAIC. These capability improvements directly promote the firm's market position and competitive advantage, thus leading to a more positive impact on the firm performance.

From the perspective of TAIC, entering the international market means that firms will face more data and information (Dam et al., 2019). This provides them with opportunities to improve their data resources and analytics capabilities. Excellent TAIC represents a firm’s ability to better collect, process. and analyse data, to gain a better understanding of international market characteristics and competitor dynamics (Joensuu-Salo et al., 2018). Data-driven decision-making also helps firms more accurately grasp opportunities in the international market (Ulman et al., 2021) and optimise the design and promotion strategies of products and services, further improving the performance. In addition, exploring international markets requires establishing more complex and extensive supply chain networks and global value chains (Strange and Zucchella, 2017). A high level of TAIC is needed to optimise firms’ production and supply chain management and reduce operating costs and risks (Wang, G. et al., 2016). Finally, international presence can prompt firms to accelerate technical innovation and product innovation (Cantwell, 2017; Silva et al., 2017; Onetti et al., 2012). When firms face a more challenging international competitive environment, they need to continuously launch new products and services with international competitive advantages. In this case, TAIC enables them to apply the latest technical achievements more quickly and improve the quality and innovation level of products and services, thereby improving firms’ market share and performance level.

6.3 Theoretical Contributions

6.3.1 Contributions to RBV

RBV is an important theory for studying the implementation of technology by organizations (Bharadwaj, 2000). Based on RBV, the survey by Ransbotham et al. (2017) found that there was a large gap between firms' expectations and real implementation of AI initiatives. The main reason is that organizations have insufficient understanding, acquisition, and utilization of AI resources (Ransbotham et al., 2017). Findings from the literature review in this study show that existing literature often overlooks the challenge of aligning technical AI advances with nontechnical business strategic goals. Some scholars have advocated that more attention should be paid to the importance of elaborating the organizational resources required to successfully deploy AI techniques (Duan et al., 2019; Dwivedi et al., 2019). By drawing on RBV, this study explores various types of resources related to firm AIC and explores which methods or factors may effectively help firms accumulate AI-related resources and enhance their TAIC and NAIC, thereby improving the overall performance.

The contributions of this study to RBV are manifold. First, the operationalization of construct formation of TAIC and NAIC, as well as their conceptualization, will help future research evaluate an organization's ability to acquire AI-related resources from a new perspective. Previous concepts of IT capabilities, BDAC, and AIC were based on the dimensions of tangible resources, intangible resources, and human/workforce skills (Bharadwaj, 2000; Gupta and George, 2016; Mikalef and Gupta, 2021). However, existing studies, literature reviews, and operational definitions of AI illustrate that there are essentially nontechnical and technical distinctions between AI research focuses in management as well as AI resources in management practices (Chowdhury et al., 2023; Cui et al., 2022; Samoili et al., 2020). Therefore, it is necessary to explore the types of organizational AI-related resources and capabilities from this perspective. NAIC measures an organization's ability to acquire and utilize resources not directly leading to the advancement of AI technique, and is mainly related to business skills and organizational change capacity. In contrast, TAIC evaluates an organization's ability to acquire and utilize resources that can directly cause the AI technical advancement, mainly including data, technology, technical skills, and basic resources. Such conceptualization enriches scholars' understanding of AIC from the RBV perspective.

Secondly, while there is a growing literature on what resources AIC may contain, little research has been done on how to facilitate access to these resources (Mikalef and Gupta, 2021). In order to address this gap in the existing literature, this study introduces multiple variables such as exploration, exploitation, leaders' AI knowledge, and institutional pressures to demonstrate their role as antecedents of AIC. Empirical research confirms that increases in exploitation strategy, coercive pressure, and mimetic pressure will prompt firms to enhance their ability to accumulate nontechnical AI resources, namely NAIC, such as business skills and organizational change capabilities, thereby improving firm performance. Exploration strategy, leaders' AI knowledge, and mimetic pressure improve performance by enhancing the firm's ability to accumulate AI technical resources, namely TAIC, such as data, technology infrastructure, technical skills, etc. In this process, data-driven culture positively moderates the relationship between exploration and TAIC while negatively moderating the one between leaders' AI knowledge and TAIC. These antecedents within and outside the organizations work together to encourage firms to actively accumulate AI-related resources and enhance their ability to take advantage of these resources. Moreover, the improvement of firm AIC is not only to cope with external institutional pressure, but also a necessary condition to achieve competitive advantage (Hossain et al., 2022; Kemp, 2023; Krakowski et al., 2023). These conclusions extend the existing theory of RBV and help understand which factors are related to the resources organizations devote to AI initiatives, and how organizations should manage and utilize these resources.

Third, recent studies have adopted RBV and confirmed the positive impact of AIC on organizational performance based on firm samples from Europe, India, and the United States (Mikalef et al., 2023; Sahoo et al., 2024; Wamba et al., 2024a ; Wamba et al., 2024b). In comparison, this study not only confirms this relationship using empirical data from firms in a new context of China's YRD region. Furthermore, this study also investigates the difference in the impact of NAIC and TAIC on firm performance. The results show that a firm's ability to acquire and utilize nontechnical AI resources is more important for improving performance, which has not been reflected in previous research. Compared with TAIC, NAIC is an indicator more related to competitive advantage and needs more attention. Barney (1991) has already stated that RBV requires the firm's resources to have VRIN characteristics. However, at that time, IT infrastructure, as a tangible resource available to everyone in the market, did not necessarily bring unique and sustainable competitive advantages to firms (Barney, 1991). Existing literature has also found that organizations need to focus not only on the acquisition of resources, but also on how to effectively integrate and use these resources to form competitive organizational capabilities (Souniemi et al., 2020). The conclusions of this study support these ideas in a new conceptual perspective. That is to say, TAIC, which includes data, technology, technical skills, and basic resources, cannot be the main basis for firms to compete. Because its corresponding resources (infrastructure, technology, and talent) that serve the advancement of AI technique and/or the ability to use these resources are more easily replicated. In contrast, business skills and organizational change capacity, namely NAIC, can create greater competitive advantages for the firm. These aspects involve the firm's unique knowledge and experience in maximizing the business value of technical resources, which is difficult to be copied or acquired by other competitors.

Fourth, whether it is NAIC or TAIC, their impacts on firm performance are both moderated by the firm international presence, and the degree of the moderating effects are similar. In other words, if a company develops international business while accumulating and utilizing AI resources, its NAIC and TAIC can both more positively affect its performance. In the current global environment, firms face fierce competition with increasing risks. Against this background, the decision-making process needs to become more rapid and effective (Elia et al., 2021). Luo (2021a) emphasizes that utilizing global resources is part of the advantages of digital open resources. This means that by leveraging AI tools and platforms, firms can better integrate and utilize global resources, thereby increasing efficiency and reducing costs. As external (global) resources become more available, firms can also more easily acquire resources on a global scale, thus improving their competitiveness (Luo, 2021b). Meanwhile, external networks also provide more value in response to the accelerated pace of global competition. By establishing close ties with partners around the world, firms can better respond to global competition and seize market opportunities (Birkinshaw, 2022). This study expands the understanding of how to more effectively transform AI resource utilization capabilities into competitive advantages by discovering the significant moderating effect of firm international presence on the relationship between AIC and firm performance.

Fifth, this study views leaders' AI knowledge as a resource within the organization and an antecedent to improving TAIC. Recently, research by Pinski et al. (2024, p.17) has found that AI literacy is an "essential executive requirement" for leaders to value the success of AI initiatives. RBV emphasizes technology as a unique strategic resource that can help firms gain sustainable competitive advantage through its use (Wernerfelt, 1984). However, the results of this study further demonstrate that even if a firm owns advanced technical resources, it still needs leaders' AI knowledge to help these resources perform the best. Such results prompt the expansion of the scope of research into AI-related resources, such as further research on whether leaders' other characteristics (e.g., education and experience) enhance the utilization of AI resources.

6.3.2 Contributions to institutional theory

It is feasible to use an institutional perspective to investigate the successful adoption of IS. However, as DiMaggio and Powell (1983) propose, companies may develop different response strategies to different institutional pressures. The focus of this study on resource-related decisions integrates RBV (Wernerfelt, 1984) and institutional theory (Oliver, 1997). This study empirically examines how different institutional pressures are related to various resource choices, which in turn affect an organization's performance. It can therefore be speculated that some resource-related decision-making factors may be affected by pressure, which will further affect the strategy for successful implementation of AI techniques. Early IS research has identified a number of potential success factors and evaluated their adoption and implementation (Akkermans and van Helden, 2002; Somers and Nelson, 2001).

In addition, a large number of studies have focused on the impact of institutional pressures on previous organizational IT capabilities (such as BDAC) (Behl et al., 2022; Dubey et al., 2019a; Hsu et al., 2012), or the institutional impact on the AI adoption stage (Bag et al., 2021). The general conclusion is that all three pressures will have a direct effect on firm BDAC development or AI adoption (Bag et al., 2022; Dubey et al., 2019a). Some conclude that normative pressures have a relatively insignificant impact on firms' adoption of new techniques (Bag et al., 2021). However, the role of institutional pressures during the application of AI in organizations has not been well studied. On the basis of constructing NAIC and TAIC, this study further investigates the impact of different institutional pressures on these two types of AIC (organizational AI application stage), thus making a contribution to institutional theory. This study proves that coercive pressure only promotes firm NAIC, mimetic pressure promotes both NAIC and TAIC, and normative pressure has no significant effect on improving both AICs.

Institutional pressure plays a very important role for firms when it comes to their use of AI techniques and sustainability practices. This study shows that institutional pressure is further promoting the utilization of AI resources by firms in China's YRD region through different influencing mechanisms. Among them, mimetic pressure proves the most prominent effect as it has a significant positive impact on both NAIC and TAIC. This means the competition in China's YRD regional market is very fierce. Another reason may be the emphasis on face (or "mianzi" in Chinese) in Chinese traditional culture. The successful performance of competitors or partners in the use of technology makes firms more eager to achieve similar success in order to avoid losing face (Huo et al., 2013). In terms of the impact on TAIC, coercive pressure from regulations and stakeholders also has a significant effect on TAIC. In emerging economies, institutional pressures, especially regulatory pressure, often have a strong influence on firms' technology use (Jabbour et al., 2020). In studies on the impact of institutional pressures on Chinese firms, the significant role of coercive pressure has also been found (Huo et al., 2013; Zhu et al., 2012; Zhu, 2016). On the other hand, normative pressure will not provide significant help in improving the AIC of Chinese firms, which is similar to the findings of some previous research (Krell et al., 2016; Lin et al., 2020; Lin et al., 2021). As discussed before, normative pressure may cause companies to be more willing to settle for the status quo or follow the rules (Durand et al., 2019), rather than proactively seeking ways to better utilize AI resources. These influencing mechanisms provide a complementary understanding of the applying institutional theory in the utilization of AI resources by firms in China's economically developed regions.

6.3.3 Contributions to AI literature

Another important contribution of this study is to expand the understanding of AI in the management context. Specifically, based on a systematic review of AI research in the business and management literature, it proposes that there is a divergence that cannot be ignored between technical and nontechnical research in this field. Based on the existing AIC theoretical framework (Mikalef and Gupta, 2021), from the perspective of technical relevance, the new concepts of NAIC and TAIC are further proposed, and the ways to improve these two different AICs and their impacts are studied. While there is much literature discussing the potential business value of AI, there is little research into what antecedents might facilitate the realization of this value (Enholm et al., 2022). To this end, this study explores multiple organizational-level and contextual-level factors and empirically tests their effectiveness as antecedents of AIC. The enhancement of AIC can also help improve organizational performance more effectively under the moderating effect of the firm's international presence. In addition, NAIC can convey the impact of organizational exploitation strategy and coercive pressures on performance, while TAIC can convey the impact of organizational exploration strategy on performance. Through empirical research and SEM analysis, this study confirms the validity of the proposed concepts and theoretical model on AIC.

First, this study examines organizational factors that promote AIC. Exploration and exploitation are common means of organizational learning (March, 1991). In recent management research, they are also understood as the ways in which organizations accumulate digital resources (Pramanik et al., 2019; Tajudeen et al., 2019). However, existing research often focuses on their impact on an organization's overall technology use (Jafari-Sadeghi et al., 2021), or studies ambidexterity, their combination, as a driver (Åkesson et al., 2018). This study focuses on the difference between exploration and exploitation, as well as their respective impacts on NAIC and TAIC, to help understand their distinct influencing mechanisms. On the one hand, exploitation can help firms obtain existing data resources and mature analysis tools, quickly improving its data processing and analysis capabilities, and thereby increase business insights (Popovič et al., 2018). Exploitation can also promote the dissemination and sharing of knowledge within the firm and strengthen employees' ability to cope with change and make decisions (Bierly III et al., 2009). In addition, exploitation helps firms establish close partnerships to achieve resource complementarity and risk sharing (Rothaermel, 2001; Yang et al., 2014), further strengthening NAIC. On the other hand, exploration can help firms obtain new resources, such as new data, technology, and knowledge (Garcia et al., 2003). Exploration can introduce or cultivate talents with excellent technical skills and enhance employees' technical level and innovation awareness (Bierly III et al., 2009). Meanwhile, exploration requires firms to invest more basic resources (time and funds) in R&D activities (Garcia et al., 2003), which helps improve TAIC. These insights provide a better understanding of which strategies firms should decide on before leveraging different types of AI resources.

Secondly, previous research usually focuses on the role of top management support or leadership in AI adoption (Chatterjee et al., 2022a; Chatterjee et al., 2022b; Jorzik et al., 2023; Shafique et al., 2024; Shao et al., 2022; Tsai et al., 2022), or study the impact of leaders' STARA competences on other variables, such as green product innovation (Ogbeibu et al., 2021; Ogbeibu et al., 2024). In the unique context of AI applications, leaders' technical knowledge begins to play an increasingly important role (Brock and von Wangenheim, 2019). This study innovatively examines leaders' AI knowledge as a direct antecedent of AIC and finds its positive impact on TAIC. Moreover, this impact conflicts with the organizational overall data-driven culture to some extent, as data-driven culture negatively moderates this relationship. Whether there are more similar conflicts and how to resolve them may become new important research questions. These conclusions make a creative contribution to research on how organizations could apply AI with the role of leaders.

Third, this study combines AI-related theory with international business practice to gain a deeper understanding of the interaction between the two. The application of AI techniques can significantly optimize the firm's decision-making process (Duan et al., 2019; Jarrahi, 2018;

Shrestha et al., 2019). By utilizing advanced AI techniques, firms can process large amounts of data faster, thus predicting market trends more accurately and making more rational strategic decisions (Caputo et al., 2022). AI techniques also enable firms to more effectively control production and value chain activities globally (Buckley and Strange, 2015; Strange and Zucchella, 2017). Through intelligent management tools and platforms, firms can monitor the operating status of each link in real time, adjust resource allocation in a timely manner, and improve overall efficiency. Those with higher AIC levels will also have a stronger ability to introduce and use new technologies globally. This can not only help firms maintain their leading positions in technical progress, but also promote changes in business models and create new market opportunities through technical innovation (Garbuio and Lin, 2019). Additionally, technique exchange within a multinational firm's global network can also significantly enhance its competitive advantage. By sharing best practices and technical solutions, firms can optimize the allocation of resources globally and enhance overall competitiveness (Zander, 1998). These findings enhance the understanding of the interplay between firm’s AI use and international development.

Last but not least, when reviewing the B&M research on AI, the researcher finds that although there are many divergences between nontechnical and technical research, great attention to the decision support function of AI appears in both literature groups. This suggests that it should be considered as a necessary characteristic or capability of AI. However, none of the existing popular AI concepts (Russell and Norvig, 2013; Kaplan and Haenlein, 2019) mention this. Specifically, literature evidence shows that many researchers have been working on optimisation techniques (Abdolraso et al., 2021). These optimisation algorithms are used for classification, prediction, optimization, and other functions which further serve the same goal - decision-making. As these algorithms enter the implementation and practical application stage, management decision-making standards may undergo revolutionary changes, and managers making optimal decisions will become a reality (Wilson and Daugherty, 2018). The development of AI technique will certainly overcome various limitations. Its powerful information processing capabilities and absolute rationality can achieve more scientific analysis and integration of data, optimize the manager's decision-making environment, break through the limitations of human factors, and thus assist managers in implementing management activities in accordance with optimal decision-making principles (Makridakis, 2017). This is also considered to be one of the ultimate goals of applying AI techniques to B&M. Current definitions of AI already recognize its two foundations: data and learning, but it is time to consider incorporating AI’s decision support function into its concept, especially from a management perspective. After all, decision-making runs through the entire management process and is the core of management work (Landry, 2020). Therefore, this study hopes to promote management research on AI to consider more decision-making demands, with the aim to ultimately form an interdisciplinary and universally acknowledged concept about AI from this view.

6.4 Practical implications

The results and findings of this study also provide inspiration and implications for managers' practice. First of all, although exploration and exploitation are both means that organizations often use together to accumulate technical resources, it is actually necessary to first distinguish whether the AI-specific resources needed are technical or nontechnical. This classification can help firms choose more appropriate strategies to accumulate and utilize the resources. Specifically, if they are nontechnical AI resources that are needed, such as improving business skills and organizational change capacity, firms should consider adopting an exploitation strategy to upgrade existing AI techniques, knowledge, and experience. If the firm requires technical AI resources, such as data, technology infrastructure, and/or technical skills, then the exploration strategy should be prioritised.

Secondly, leaders’ AI knowledge is also important to firms’ TAIC. This study proves that leaders with higher levels of AI knowledge can help firms better build up technical resource advantages. Therefore, if organizations want to make progress in AI techniques, managers should actively increase their own AI knowledge. Or they can consider introducing members with rich AI expertise to the top management team to serve as CDOs and other similar positions to provide important assistance to the organization's technical decisions.

The role of data-driven culture cannot be ignored either. While firms are developing TAIC, they need to balance the relationship between data-driven culture and other factors within the organization. This culture is helpful for organizations to improve TAIC when they explore new techniques and knowledge about AI. However, if leaders also have sufficient AI knowledge reserves themselves, this will conflict with a highly data-driven culture and be detrimental to the development of TAIC. Therefore, how to balance this contradictory and delicate relationship will become a difficult problem for managers.

In terms of institutional pressures, managers also need to develop appropriate strategies to deal with different types of pressures. Mimetic pressure will have a direct impact on both NAIC and TAIC. Therefore, managers can learn more about the successful cases of competitors, thereby prompting their own organizations to refer to these successful experiences, in order to gain AIC reinforcement and ultimately improve organizational performance. Of course, this also means that when firms succeed in AI applications, they will be imitated by more competitors. Firms need to think about how to maintain their competitive advantages through innovation in AI techniques and knowledge. In addition, coercive pressure will have a positive impact on NAIC. Therefore, managers need to understand how to use data and technology appropriately by ensuring regulatory compliance. Privacy protection and data fairness are the issues that regulations attach great importance to. Managers should take these factors into consideration when formulating AI application strategies.

Finally, managers can believe that both NAIC and TAIC have a significant impact on firm performance. When firms' technical and nontechnical resources are imbalanced, managers should give priority to the role of NAIC because it affects firm performance to a greater extent. From this perspective, managers first need to learn to distinguish between TAIC and NAIC. This study's conceptual construction of the two provides a reference for managers. The moderating role of a firm's international presence is also important. Those without international business should consider the positive impact of this option on AIC's mechanism for improving performance. Firms that are already involved in international business should continue to maintain it to promote the positive effect of AIC on firm performance.

6.5 Implication for policy makers

Since this study incorporates coercive pressure which means pressure from government laws, regulations, and supervision, it is necessary to discuss the implications for policy making. The government affects firms' activities in nontechnical AI resources, namely NAIC, by formulating and enforcing legal and regulatory frameworks. These regulations may include provisions on intellectual property protection, data privacy protection, market access conditions, etc., which directly affect firms' strategic decisions. Coercive pressure from laws and regulations forces firms to pay more attention to legal business activities. Therefore, firms also have to review and optimise their organizational structures, management processes, and business models to comply with regulatory requirements. Under such pressure, firms will strengthen risk management, especially the timely identification, assessment, and response to possible legal risks. Considering these, the government should formulate clear laws, regulations, and/or policies based on industry characteristics and technical development trends to provide clear reference standards for enterprises. A sound legal system needs to be established to promote firm compliance operations and maintain market order and public interests. Relevant departments should strengthen supervision and law enforcement, and improve the intensity and efficiency of investigating and punishing violations. The government can also strengthen the publicity of laws and regulations to firms and the public. Official guidance can be provided through interpretation of legal policies and training to improve firms' awareness and understanding of regulations, thereby more effectively improving their NAIC.

6.6 Chapter summary

This chapter further revealed and explained the meaningful findings brought about by the data analysis results. It was finally determined that the antecedents of firm NAIC include exploitation strategy, coercive pressure, and mimetic pressure. The antecedents of firm TAIC include exploration strategy, leaders' AI knowledge, and mimetic pressure. Data-driven culture plays a different mediating role in these. Firms' NAIC and TAIC levels will positively affect firm performance under the moderation of international firm presence. These findings make significant contributions to RBV, institutional theory, and AI research in the management field. It also provides insightful implications for managers and policy makers.

Chapter 7: Conclusion

7.1 Answering the research questions

Chapter 1.4 proposed the specific research questions in accordance with the research aims and objectives. Based on the results and findings from this study, conclusive answers can now be given to these questions.

1. To what degree do different organizational (exploration, exploitation, leaders' AI knowledge) and contextual (institutional pressures) factors influence firms' nontechnical and technical AIC development?

At the organizational level, exploitation would positively affect firms' NAIC (nontechnical AIC) development. Exploration and leaders' AI knowledge would have a positive impact on firms' TAIC (technical AIC) development. At the contextual level, coercive pressure would positively influence firms' nontechnical AIC. Mimetic pressure would have direct positive effects on both nontechnical and technical AIC.

2. To what degree does firms' nontechnical and technical AIC development influence firm performance, and is this relationship moderated by any factors?

Firm's NAIC and TAIC both positively influence firm performance to a very significant extent. Both of the relationships are positively moderated by firms' international presence.

3. What is the difference between how nontechnical and technical AIC are affected by the antecedents and how they impact firm performance?

Exploration has a significant positive impact on firm TAIC but not NAIC. Exploitation acts the opposite (significant on NAIC rather than TAIC). Leaders' AI knowledge only facilitates development of TAIC, with no observable effect on NAIC. Meanwhile, organizational data-driven culture enhances the impact of exploration and weakens the impact of leaders' AI knowledge on firm TAIC.

Coercive pressure positively influences firms' NAIC only. Normative pressure affects neither NAIC nor TAIC. Mimetic pressures would positively impact both NAIC and TAIC to almost the same extent.

NAIC would have a much more significantly positive relationship than TAIC whose relationship with firm performance is also very significantly positive. Meanwhile, firm international presence enhances these two relationships.

7.2 Limitations

It must be admitted that this study still has some limitations which may not be conducive to the generalisation of the results and findings. Firstly, through a methodological lens, this study adopted the quantitative research method. As discussed in chapter 4.4, the quantitative method uses survey questionnaires as means of data collection which does not allow respondents to express their opinions freely (Patton, 2002). Thus quantitative methods may ignore potential insights generated by respondents if they are surveyed in a qualitative way such as semi-structured interview (Adeoye-Olatunde and Olenik, 2021). The regional scope of the sample was also limited to firms located in the YRD region of China. Although YRD firms represent the most advanced level of AI development and application in China, they cannot represent the AI application level of firms all across China, or the rest of the world. Besides, the choice of cross-sectional time horizon only allowed this study to investigate the empirical evidence at a single time point (Koufteros et al., 2014). It could not explain the evolution of AIC's effect mode at different stages, especially over the long term.

Secondly, from the perspective of research hypotheses and proposed model, this study did not consider the interplay between NAIC and TAIC, which would be an interesting topic. The researcher used STARA competences to measure leaders’ AI knowledge, which only took into account the AI knowledge of technical aspects. Leaders’ AI knowledge could actually incorporate more relevant elements.

Finally, regarding the results, this study did not take into account all the background information collected from the sample firms. Some other characteristics of firms and/or respondents (leaders) could be potential variables to consider.

7.3 Future research directions

Corresponding to the limitations, this study also provides suggestions for future research. First, research methods can be improved. Future research can further relevant discussions on AIC based on a wider regional scope and firm samples or conduct comparative studies in different scopes. It is recommended to use qualitative methods or mixed methods to obtain additional insights from practitioners. Longitudinal studies are also needed to investigate how AIC changes and develops over time. Second, the research model can be further extended. More potential antecedents of AIC should be considered and hypothesized, such as the type of AI techniques used by firms, whether executive positions for technology management are set up, and the respondent's education level and overseas experience, etc. The potential effects of these factors on AIC deserve to be analysed and studied one by one. It is also worth considering adding other moderators to the existing model and relationships. For example, this study only investigated the moderating effect of firm international presence as a categorical variable. Future research could attempt to examine the quantitative moderating effects of the degree of internationalization (dimensions such as speed and scale). The contradictory effect between DDC and LAIK is also an interesting phenomenon that needs to be further studied and explained. Finally, future research should try to introduce more relevant theories to generate more hypotheses. From the perspective of institutional theory alone, this study only adopted its most commonly used aspect, that is, the impact of institutional pressures. However, it is necessary to discuss whether institutional isomorphism (DiMaggio and Powell, 1983) will lead firms to adopt the same resource strategy in the long run; and in order to maintain competitiveness, how firms can implement diversified strategies in the improvement of NAIC and TAIC. Through future research in these potential directions, it is expected to further enrich relevant theories and expand AI research results in the field of management.

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Appendices

Appendix 1 Letter of Ethics Approval

College of Business, Arts and Social Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

23 November 2022

LETTER OF APPROVAL

APPROVAL HAS BEEN GRANTED FOR THIS STUDY TO BE CARRIED OUT BETWEEN 23/11/2022 AND 31/12/2023

Applicant (s): Mr Zequn Cui

Project Title: Impact of artificial intelligence capability on firm performance: from nontechnical and technical perspectives

Reference: 40256-LR-Nov/2022- 42065-1

Dear Mr Zequn Cui

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has agreed that there is no objection on ethical grounds to the proposed study. Approval is given on the understanding that the conditions of approval set out below are followed:

A18 – Under "What are the indemnity arrangements?" delete the text that you currently have and instead state the following, "Brunel University London provides appropriate insurance cover for research which has received ethical approval."

- **The agreed protocol must be followed. Any changes to the protocol will require prior approval from the Committee by way of an application for an amendment.**
- **Please ensure that you monitor and adhere to all up-to-date local and national Government health advice for the duration of your project.**

Please note that:

- Research Participant Information Sheets and (where relevant) flyers, posters, and consent forms should include a clear statement that research ethics approval has been obtained from the relevant Research Ethics Committee.
- The Research Participant Information Sheets should include a clear statement that queries should be directed, in the first instance, to the Supervisor (where relevant), or the researcher. Complaints, on the other hand, should be directed, in the first instance, to the Chair of the relevant Research Ethics Committee.
- Approval to proceed with the study is granted subject to receipt by the Committee of satisfactory responses to any conditions that may appear above, in addition to any subsequent changes to the protocol.
- The Research Ethics Committee reserves the right to sample and review documentation, including raw data, relevant to the study.
- If your project has been approved to run for a duration longer than 12 months, you will be required to submit an annual progress report to the Research Ethics Committee. You will be contacted about submission of this report before it becomes due.
- You may not undertake any research activity if you are not a registered student of Brunel University or if you cease to become registered, including abeyance or temporary withdrawal. As a deregistered student you would not be insured to undertake research activity. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Professor David Gallear

Chair of the College of Business, Arts and Social Sciences Research Ethics Committee

Appendix 2 Survey Questionnaire (original version)

Part 1. Basic info (Control variables)

Construct	Measurement	Sources
1. Firm Age	Q: When is your firm established? A: ______ (Firm here refers to the strategic business unit you work in. It could be either an independent company, or a subsidiary of a larger corporation.)	Mikalef et al., 2021 Qian and Li, 2003
2. Firm Size	Q: What is the number of employees in your company? A:1-9, 10-49 50-249, 250 +	Mikalef et al., 2021
3. Industry	Q: In which industry sector does your company operate in? A: Manufacturing Service provider Consultancy Financial services Energy, utilities and resources Retail and consumer goods Information technology Media and communication services Transport Others______	Kristoffersen et al., 2021
4. Product/Service	Q: Does your firm manufacture physical products or provide services as main business? A: Manufacturing (1) Service (0)	Liu et al., 2013 Mikalef et al., 2021

	Q: How many products/services does your company provide? A: 1-3 4-6 7-10 >10	Grover and Saeed, 2007
5. Ownership	Q: What is the ownership type of your company? A: State-owned (the state or its agencies are the ultimate owner or the largest shareholder of your firm) Privately-owned (invested or controlled by a natural person and based on wage labor) Collectively-owned (part of the employees collectively own the means of production, work together and distribute according to work) Foreign-invested (Joint investment by Chinese investors and foreign investors, or separate investment by foreign investors)	Zhou and Van Witteloostuijn, 2010; Tan, 2002
	Q: Does this business unit belong to a parent company? A: No. Yes, it belongs to a UK-based parent company. Yes, it belongs to a non-UK-based parent company, and the country origin of the parent company is ________.	
6. International presence	7.1 Q: Does your company have relations with foreign countries? A: Yes, it sells abroad → go to question 7.2 Yes, it buys from abroad → go to question 8 No → go to question 8	Denicolai et al., 2021
	7.2 Q: What is the percentage share of foreign sales on the total turnover? A: Between 0 and 10%	

	Between 10 and 30% Between 30 and 50% Between 50 and 70% Between 70 and 100%	
7. Leadership setting	Q: Has your company set one of the following positions: CDO (Chief Digital Officer - a senior executive position dedicated to digital issues) CTO (Chief Technology Officer - senior executive responsible for technical matters in the corporation) CIO (Chief Information Officer - senior executive responsible for information technology matters) A: Yes None Other similar positions	Kunisch et al., 2020;
8. Firm's AI experiences	Q: How long has your company been using AI technologies? A: < 1 year 1 – 2 years 2 – 3 years 3 – 4 years 4 + years	Mikalef et al., 2023
	Q: Based on function, what type of AI technologies does your company mainly use? A: Conversational AI (refers to the general capability of computers to understand and respond with natural human language as it is written or spoken) Biometric AI (AI-powered biometrics uses applications such as facial recognition, speech recognition and computer vision for identification, authentication, and security objectives in computer devices, workplace, and home security, among others)	Benbya et al., 2021

	Algorithmic AI (use of machine learning algorithms trained on structured data and specific to narrow task domains, such as speech recognition and image classification. or deep learning neural networks that are able to learn from large volumes of labelled data, enhance themselves by learning, and accomplish a variety of tasks such as classification, prediction, and recognition) Robotic AI (physical robots used to perform dedicated tasks in factory automation)	
9. Respondent's position	Q: What is your position within the company? A: CEO/President (top executive in the company, responsible for overall company strategy and execution) CIO CDO CTO Director (appointed or elected member of the board of directors of the company) Manager (in charge of a department in the company) Other______	Mikalef et al., 2023
10. Respondent's education background	Q: What is your education background? A: Primary school Secondary school High school Bachelors' degree Masters' degree PhD Other______	Rialti et al., 2019
	Q: Do you have any overseas education/work experiences? A: Yes, I have only studied overseas before.	Tihanyi et al., 2000

	Yes, I have only worked overseas before. Yes, I have both studied and worked overseas before. No, I have neither studied nor worked overseas before.	
11. Respondent's AI experiences	Q: From 1 (strongly disagree) to 7 (strongly agree), to what extent do you think you have good knowledge of AI technologies: LAIK1. I have the knowledge and ability to apply smart (analysing, reporting and self-monitoring systems) technology during operations. LAIK2. Matters related to machines that share similar qualities (learn, reason, discover and calculate) with the human mind could be adequately addressed by me. LAIK3. I know how to design and apply robots or mechanical devices during operations.	Ogbeibu et al., 2021
	Q: How many years of experiences do you have in using AI techniques? A: < 1 year 1–2 years 2–3 years 3–4 years 4+ years	Mikalef et al., 2019

Part 2. (Independent variables)

(1) Firm-level independent variables (exploration/exploitation strategies, organizational culture)

Construct	Measurement (7-point Likert scales, 1-strongly disagree, 7-strongly agree)	Sources

	From 1 to 7, to what extent do you agree with the following statements	
Exploitation	Since your company adopted AI technologies, your company has: EXPT1. Upgraded current knowledge and skills for familiar products and technologies. EXPT2. Invested in enhancing skills in exploiting mature intelligent technologies that improve the business process. EXPT3. Enhanced competencies in searching for intelligent solutions to customer problems that are near to existing solutions rather than completely new solutions. EXPT4. Upgraded skills in business processes in which the firm already possesses significant experience. EXPT5. Strengthened our knowledge and skills for projects that improve efficiency of existing business activities.	Wang and Rafiq, 2014 (Adapted from Atuahene-Gima, 2005 and Zahra et al., 2000)
Exploration	Since your company adopted AI technologies, your firm has: EXPR 1. Acquired AI technologies and skills entirely new to the firm.	Wang and Rafiq, 2014 (Adapted from Atuahene-Gima, 2005 and Zahra et al., 2000)

	EXPR 2. Learned AI technologies entirely new to the industry. EXPR 3. Acquired entirely new managerial and organizational skills that are important for AI application (such as forecasting technological and customer trends; identifying emerging markets and technologies; coordinating and integrating R&D; marketing, manufacturing, and other functions; managing the product development process)/ EXPR 4. Learned new skills in areas such as funding AI technology, staffing R&D function, training and development of R&D, and engineering personnel for the first time. EXPR 5. Strengthened technological capabilities in areas where it had no prior experience.	

Construct	Measurement (7-point Likert scales, 1-strongly disagree, 7-strongly agree)	Sources

Data-driven culture	From 1 to 7, to what extent you agree that in your company: DDC1. We consider data a tangible asset. DDC2. We base our decisions on data rather than on instinct. DDC3. We are willing to override our own intuition when data contradict our viewpoints. DDC4. We continuously assess and improve the business rules in response to insights extracted from data. DDC5. We continuously coach our employees to make decisions based on data.	Yu et al., 2021 Dubey et al., 2019b (Both adapted from Gupta and George, 2016)

(2) Context-level independent variables (institutional pressures)

Construct	**Measurement (7-point Likert scales, 1-strongly disagree, 7-strongly agree)** **From 1 to 7, to what extent do you agree with the following statements**	**Sources**
Coercive pressures	CP 1. The data protection law requires our firm to use data safely.	Dubey et al.,2019a

	CP 2. The industry association requires us to use data within the boundary of regulatory norms. CP 3. The stakeholders of our firm want us to exploit data to improve decision making without interfering into privacy of any individuals, which may attract defamation to the firm. CP 4. Regulation and policy determinants influence and motivate consumers' and suppliers' implementation of AI technologies. CP 5. Policy makers propose instruments to decrease resource demand for implementing AI technologies. CP 6. Regulation and policy determents support the development of innovative solutions for implementing AI technologies. CP 7. Regulation and policy determents support economic incentives for implementing AI technologies. CP8. Successful economic incentives may drive the implementation of AI technologies.	Bag et al., 2022

Normative pressures	NP1. Our firm's suppliers using AI technologies influences our firm to use AI technologies. NP2. Our firm's customers using AI technologies influences our firm to use AI technologies. NP3. The industry associations' promotion of AI influences our firm to use AI technologies.	Dubey et al., 2019a (Adapted from Liang et al., 2007)
Mimetic pressures	MP1. Our competitors who have adopted AI have greatly benefitted. MP2. Our competitors who have adopted AI are favourably perceived by the others in the same industry. MP3. Our competitors who have adopted AI are favourably perceived by their suppliers and customers.	Dubey et al., 2019a (Adapted from Liang et al., 2007)

Part 3. AI capability

Construct	Measurement (7-point Likert scales, 1-strongly disagree, 7-strongly agree) From 1 to 7, to what extent do you agree with the following statements	Sources
Tangible		

Data	DATA1. We have access to very large, unstructured, or fast-moving data for analysis DATA2. We integrate data from multiple internal sources into a data warehouse or mart for easy access DATA3. We integrate external data with internal to facilitate high-value analysis of our business environment DATA4. We have the capacity to share our data across organizational units and organizational boundaries. DATA5. We are able to prepare and cleanse AI data efficiently and assess data for errors DATA6. We are able to obtain data at the right level of granularity to produce meaningful insights	Mikalef et al., 2021 Mikalef et al., 2023
Technology	TECH1. We have explored or adopted cloud-based services for processing data and performing AI and machine learning TECH2. We have the necessary processing power to support AI applications (e.g., CPUs, GPUs) TECH3. We have invested in networking infrastructure (e.g., enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency) TECH4. We have explored or adopted parallel computing approaches for AI data processing	

	TECH5. We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g., Microsoft Cognitive Services, Google Cloud Vision) TECH6. We have invested in scalable data storage infrastructures TECH7. We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology	
Basic Resources	BR1. Our AI initiatives are adequately funded BR2. Our AI project has enough team members to get the work done BR3. Our AI project is given enough time for completion	
Human Skills		
Technical Skills	TS1. Our company has access to internal talent with the right technical skills to support AI work TS2. Our company has access to external talent with the right technical skills to support AI work TS3. Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning) TS4. Our data scientists have the right skills to accomplish their jobs successfully	

	TS5. Our data scientists are effective in data analysis, processing, and security TS6. Our data scientists are provided with the required training to deal with AI applications TS7. We hire data scientists that have the AI skills we are looking for TS8. Our data scientists have suitable work experience to fulfil their jobs	
Business Skills	BS1. Our managers are able to understand business problems and to direct AI initiatives to solve them BS2. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our company BS3. Our managers have a good sense of where to apply AI BS4. The executive manager of our AI function has strong leadership skills BS5. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs BS6. Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and citizens	

	BS7. We have strong leadership to support AI initiatives. BS8. Our managers demonstrate ownership of and commitment to AI projects. BS9. Our managers demonstrate an exemplary attitude to the use of AI.	
Intangible		
Inter-Departmental Coordination	From 1 to 7, please indicate to what extent do departments (e.g., marketing, R&D, manufacturing, information technology, and sales) within your organization engage in the following activities: IDC1. Collaboration IDC2. Collective goals IDC3. Teamwork IDC4. Same vision IDC5. Mutual understanding IDC6. Shared information IDC7. Shared resources	
Organizational Change Capacity	OCC1. Our organization is able to anticipate and plan for the organizational resistance to change. OCC2. Our organization follows appropriate regulations when reengineering processes.	

	OCC3. Our organization acknowledges the need for managing change. OC4. Our organization is capable of communicating the reasons for change to the members of our organization. OC5. Our organization is able to make the necessary changes in human resource policies for process re-engineering. OC6. Our management commits to new values in our organization.	
Risk Proclivity	RP1. In our organization we have a strong proclivity for high-risk projects (with chances of very high returns) RP2. In our organization we take bold and wide-ranging acts to achieve firm objectives RP3. We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities.	

Part 4. Firm performance

Construct	**Measurement (7-point Likert scales, 1-strongly disagree, 7-strongly agree)** **From 1 to 7, to what extent do you agree with the following statements**	**Sources**

Firm Performance	Compared to our key competitors, since we adopted AI technologies: FP1. Our firm has been more successful. FP2. Our firm has achieved a greater market share. FP3. Our firm has been growing faster. FP4. Our firm has been more profitable. FP5. Our firm has been more innovative. FP6. Our firm has reached higher return on investment (ROI). FP7. Our firm has decreased the product or service delivery cycle time. FP8. Our firm has got more rapid response to market demand change. FP9. Our firm has more rapid confirmation of customer orders. FP10. Our firm has got more increase in customer satisfaction. FP11. Our firm has entered new markets more quickly. FP12. Our firm has got higher success rate of new products or services.	Lee and Choi, 2003 Liu et al., 2013 (Adapted from Rai et al. (2006) and Chen, Paulraj, and Lado (2004)) Wamba et al., 2017 (Adapted from Tippins and Sohi (2003) and Wang et al., (2012))

Appendix 3 Survey Questionnaire (translated version)

人工智能与公司绩效调研
Page 1: 感谢您的参与
非常感谢您参与本次调查！您提供的回答将被妥善保管和处理，如有任何疑问或建议请根据问卷结束后提供的联系方式与我们联系。
本问卷中的每道题均为必答题，无法跳过，作答完成后方可提交，感谢您的理解配合！

Page 2: 第一部分：公司基本信息
注：本问卷中的"公司"均指您所在的战略业务单元，即一个独立的公司或附属于母公司的一个子公司。

*1.*贵公司成立的时间是？（请填写年份） *Required*

*2.*贵公司有多少员工？ *Required*
1-9 人
10-49 人
50-249 人
多于 250 人

*3.*贵公司属于什么行业？ *Required*
制造业
服务业
金融服务
能源、公用事业和资源
零售和消费品
信息技术
传媒
交通运输
其它

*a.*如果选择"其它"，请写明具体行业：

*4.*贵公司是以产品制造还是服务供应作为主要业务？ *Required*
产品制造
服务供应
两者都为主要业务
以其他业务为主要业务

*a.*贵公司的主要业务为：

*5.*贵公司主要提供多少种产品/服务？ *Required*
1-3
4-6
7-10

>10

*6.*贵公司属于哪种所有制的企业？ *Required*
国有企业（国家或地方政府是公司的实际所有者或最大股东）
私营企业（由自然人投资或控制，以雇佣劳动为基础）
集体企业（部分员工集体拥有生产资料，共同工作，按劳分配）
外资企业（由外国投资者单独投资或中国与外国投资者共同投资）

*7.*贵公司是否附属于某家母公司？ *Required*
本公司不附属于任何母公司
是的，它附属于一家中国的母公司。
是的，它附属于一家英国的母公司。
是的，它附属于一家其他国家/地区的母公司

*a.*请写出母公司所在的具体国家/地区：

*8.*贵公司是否有海外进出口业务？ *Required*
是，向海外出口
是，从海外进口
是，进出口业务都有
否

*a.*贵公司的海外销售额占总销售额的比例大约是多少?
0-10%
10-30%
30-50%
50-70%
70-100%

*9.*请问贵公司是否设置了以下职位（可多选）： *Required*
首席数字官（CDO）
首席技术官（CTO）
首席信息官（CIO）
没有上述职位
有其他信息技术相关的管理职位

*a.*职位名称：
注：定义
CDO （首席数字官：专门负责数字技术事项的高管）
CTO（首席技术官：专门负责科技事项的高管）
CIO（首席信息官：专门负责信息技术事项的高管）

*10.*贵公司有多长时间使用人工智能技术的经验？ *Required*
小于 1 年
1-2 年
2-3 年

3-4 年
大于 4 年

*11.*基于功能分类，贵公司主要使用哪些人工智能技术？（可多选） *Required*
对话式人工智能
生物识别人工智能
算法人工智能
机器人人工智能

注：定义
对话式人工智能：指计算机以书面或口头形式理解和响应人类自然语言的一般能力。
生物识别人工智能：指使用面部识别、语音识别和计算机视觉等应用，用于计算机设备、工作场所和家庭安全等方面的识别、认证和安保等目的。
算法人工智能：指使用结构化数据训练的机器学习算法或者深度学习神经网络，它能够从大量标记数据中学习，通过学习来增强自己，并完成各种任务，如分类、预测和识别。
机器人人工智能：指用于在工厂自动化中执行专门任务的物理机器人。

Page 3: 第二部分：填写人信息

*12.*您在贵公司的职位是？ *Required*
CEO/President 总裁/董事长
CDO 首席数字官
CTO 首席技术官
CIO 首席信息官
Director 董事会成员
Manager 部门经理
其他

*a.*其他职位：

*13.*您的学历是？ *Required*
小学
初中
普通高中
职业高中（中专、技工学校、技师学院等）
高职高专
普通本科
职教本科
硕士研究生
博士研究生
其他

*a.*其他学历：

*14.*您是否有过海外留学/工作经历？ *Required*
是，我只在海外留学过

是，我只在海外工作过
是，我在海外留学和工作过
否，无海外经历

*15.*您本人有多少年使用人工智能技术的经验？ *Required*
我没有任何人工智能技术的相关经验
小于 1 年
1-2 年
2-3 年
3-4 年
4 年以上

*16.*从 1（非常不同意）到 7（非常同意），请选择您在多大程度上认同以下关于您对人工智能技术精通程度的表述：

	Required						
	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意
我具备在公司运营中应用智能技术（分析、报告和自我监控系统等）的知识和能力。							
我可以完全解决与人类思维具有相似特质（学习、推理、发现和计算）的机器相关的问题。							
我知道如何在操作中设计和应用智能机器人或设备。							

Page 4: 第三部分

*17.*从 1（非常不同意）到 7（非常同意），请选择您在多大程度上认同以下关于贵公司的表述： **为提高人工智能技术水平，我们公司——**

	Required						
	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意
为公司已经掌握的产品和技术升级相关知识和技能							
加大投资用以提高公司技术水平，利用现有成熟的智能技术来改进业务流程							

为满足客户需求，努力增强寻找智能解决方案的能力，但这些解决方案接近现有方案，而非全新的方案							
在已经拥有丰富经验的业务流程方面增强我们的技能							
在提高现有业务效率的项目上加强我们的知识和技能							
学习和开发对公司来说全新的人工智能技术和技能							
学习对行业来说全新的人工智能技术							
学习和开发对实施人工智能技术非常重要的全新的管理和组织技能（预测技术和客户趋势、识别新兴市场和技术、协调和整合研发、营销和制造、管理产品开发过程等）							
在人工智能技术投资、研发人员配置、研发培训、技术人事等领域第一次学习新技能							
在没有经验的领域加强技术能力							
认为数据是一项重要资产							
依靠数据而不是直觉来做出决策							
当数据与我们的直觉观点相矛盾时，我们愿意推翻自己的直觉							
不断评估和改进业务规则，以响应从数据中提取的见解							
不断培训提高员工基于数据做出决策的能力							

Page 5: 第四部分

*18.*从 1（非常不同意）到 7（非常同意），请选择在多大程度上您认同以下表述：

	Required						
	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意

国内的数据保护相关法规要求我们公司安全地使用数据。						
国内行业协会要求我们公司在监管规范的范围内使用数据。						
公司的利益相关者希望我们利用数据来改善决策，而不干涉任何个人隐私，否则可能会给公司带来不良影响。						
国内监管政策等因素影响并鼓励我们的客户和供应商使用人工智能技术。						
政策制定者提出了相关政策，以减少实施人工智能技术所需资源。						
国内监管和政策压力促使公司开发实施人工智能技术的创新解决方案。						
国内法律政策规定了是否对实施人工智能技术给予经济上的激励。						
成功的经济激励措施可能会推动人工智能技术的实施。						
供应商对人工智能技术的使用影响我们公司对人工智能技术的使用。						
客户对人工智能技术的使用影响我们公司对人工智能技术的使用。						
行业协会对人工智能技术的推广影响我们公司对人工智能技术的使用。						
采用人工智能技术的竞争对手已经受益匪浅。						
采用人工智能技术的竞争对手被同行们视为是有利的。						
采用人工智能技术的竞争对手被其供应商和客户视为是有利的。						

Page 6: 第五部分

29.从 1（非常不同意）到 7（非常同意），请选择您在多大程度上认同以下关于贵公司的表述：

	Required						
	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意
我们公司可以访问大量的、非结构化的、快速的数据并进行分析							
我们公司将来自多个内部源的数据集成到数据库或数据集市中，以便于访问							
我们公司将外部数据与内部数据集成在一起，以促进对业务环境的高价值分析							
我们公司有能力跨组织单位和组织边界来共享我们的数据							
我们公司能够有效地准备和清理人工智能数据，并评估数据中的错误							
我们公司能够获得适当粒度级别的数据，从而产生有意义的见解							
我们公司已经探索或采用了云服务来处理数据、执行人工智能和机器学习							
我们公司有必要的处理能力来支持人工智能应用程序（如 CPU、GPU 等）							
我们公司已经在网络基础设施上进行了投资，以支持应用程序的效率和规模（可伸缩性、高带宽和低延迟）							
我们公司已经探索或采用了并行计算方法来处理人工智能数据							
我们公司已经投资使用先进的云服务，允许通过简单的 API 调用实现复杂的人工智能功能（如阿里云、华为云等）							

我们公司投资了可扩展的数据存储基础设施							
我们公司已经探索了人工智能基础设施，以确保使用最先进的技术从端到端保护数据							
我们有充足的资金支持人工智能项目							
我们有足够的团队成员来完成工作人工智能项目							
我们有足够的时间完成人工智能项目							

Page 7: 第六部分

*20.*从 1（非常不同意）到 7（非常同意），请选择您在多大程度上认同以下关于贵公司的表述：

	Required						
	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意
我们公司内部有合适的技术人才来支持人工智能工作							
我们公司能获得具有适当技术才能的外部人才来支持人工智能工作							
我们的数据专家非常擅长使用人工智能技术（如机器学习、自然语言处理、深度学习）							
我们的数据专家拥有成功完成工作所需的技能							
我们的数据专家在数据分析、处理和安全方面非常有用							
我们的数据专家接受过处理人工智能应用所需的培训							
我们公司聘用拥有人工智能技能的数据专家							

我们的数据科学家有合适的工作经验来完成他们的工作							
我们的管理人员能够理解业务问题，并指导相关人工智能项目来解决这些问题（此处“管理人员”指负责 AI 战略单元的领导，下同）							
我们的管理人员能够与数据专家、其他员工和客户合作，确定人工智能可能给我们公司带来的机会							
我们的管理人员很清楚在哪里应用人工智能							
我们人工智能部门的执行经理有很强的领导能力							
我们的管理人员能够预测职能经理、供应商和客户未来的业务需求，并主动设计人工智能解决方案来支持这些需求							
我们的管理人员能够以支持公司、供应商和员工的方式协调与人工智能相关的活动							
我们公司有强有力的领导来支持人工智能项目							
我们的管理人员直接负责并承诺投入人工智能项目							
我们的管理人员在使用人工智能方面有积极的态度，并能作出表率							

*21.*关于贵公司应对人工智能技术使用带来的组织变革，从 1（非常不同意）到 7（非常同意），请选择您在多大程度上认同以下表述：

	Required						
	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意
我们能够预测和应对公司内部对变革的抵制							
我们在重新设计业务流程时遵循适当的程序和规定							

我们认识到有效应对这些变革的必要性							
我们能够将变革的原因传达给公司成员							
我们能够对人力资源政策进行必要的变革，以进行流程再造							
我们的管理层致力于在公司中实现新的价值观							
我们对高风险项目（伴随高回报的机会）有很强的倾向							
我们采取大胆和广泛的行动来实现坚定的目标							
我们通常会采取大胆进取的姿态，以最大限度地利用潜在机会							

Page 8: 第七部分

*22.*从 1（非常少）到 7（非常多），请指出贵公司内部各部门（如市场、研发、制造、信息技术和销售）参与以下活动的程度:

	Required						
	1 非常少	2 少	3 比较少	4 不确定	5 比较多	6 多	7 非常多
协作							
集体目标							
团队合作							
共同愿景							
相互了解							
信息共享							
资源共享							

Page 9: 第八部分

*23.*从 1（非常不同意）到 7（非常同意），请选择您在多大程度上认同以下关于贵公司的表述： **自从采用人工智能技术以来，与我们的竞争对手相比——**

	Required

	1 非常不同意	2 不同意	3 比较不同意	4 不确定	5 比较同意	6 同意	7 非常同意
我们公司更成功。							
我们公司获得了更大的市场份额。							
我们公司发展得更快了。							
我们公司的利润增加了。							
我们公司更具有创新性了。							
我们公司已达到较高的投资回报率(ROI)。							
我们公司缩短了产品/服务的交付周期。							
我们公司对市场需求的变化反应更迅速。							
我们公司能更快地确认客户订单。							
我们公司的顾客满意度有了很大的提高。							
我们公司进入新市场的速度更快了。							
我们公司新产品或新服务的成功率更高。							

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非常感谢您的参与！如有疑问请发送邮件至 zequn.cui@brunel.ac.uk 与我们进行联系。

Appendix 4 Cover Letter for Survey

Dear Sir or Madam,

I am a doctoral research student pursuing my PhD in Brunel University London, UK. My research is generally about application of artificial intelligence (AI) in business and management. The title of my research is "Impact of artificial intelligence capability on firm performance: from nontechnical and technical perspectives". Specifically, the research aims to reveal how firms develop their AI capability which would impact the firm performance and explain it from nontechnical and technical perspectives, thus filling a research gap in the literature.

As part of the research, I need to collect data from companies using AI technologies through a survey questionnaire. The survey is self-administered and has been developed using a predefined scale that facilitates easiness in completing the survey. The potential participants include Chinese high-tech enterprises recognized by the government and your client companies from the high-tech industry. I would like to collaborate with you to get in touch with these companies and obtain their consent to take part in the survey. The survey will be conducted mainly by myself.

I would greatly appreciate it if you could grant permission for me to work with you and help me to conduct survey on these companies. By granting the permission, you would offer me necessary assistance in contacting the participants, including sharing their contact information with me and allowing me the access to communicating with them. The use of email addresses and other contact information will be strictly in line with both UK and China's Data Protection legislation. Your permission also means you acknowledge that the results of this research will be used to fulfill the requirements for the PhD's thesis at Brunel University London.

I would like to use and reproduce the response from participants under the following conditions:

1) I will use the survey only for my research study and will not sell or use it for any other purposes;

2) I will include a statement of attribution and copyright on all copies of the instrument. If you have a specific statement of attribution that you would like for me to include, please provide it in your response.

3) At your request, I will send a copy of my completed research study to you upon completion of the study and/or provide a hyperlink to the final manuscript.

If you do not control the copyright for these materials, I would appreciate any information you can provide concerning the proper person or organization I should contact. If these are acceptable terms and conditions, please indicate so by replying to me through e-mail via the address provided below.

If you require any clarification, please do not hesitate to contact me via the e-mail and/ or telephone details below. Thanking you for your kind cooperation and support for this important study.

Yours sincerely,

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Mobile: +447529149090