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RESEARCH ON THE IMPACT OF AI TECHNOLOGY ADOPTION ON ORGANIZATIONAL RESILIENCE OF SERVICE ENTERPRISES

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I hereby declare that this PhD dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information which have been used in this dissertation.

This PhD dissertation has also not been submitted for any degree in any university previously.

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Research on the Impact of AI Technology Adoption on Organizational Resilience of Service Enterprises

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Abstract

In a time of frequent global economic fluctuations, understanding how service enterprises can sustain stability amid fluctuating environments, and even thrive during crises, has become a significant research focus within the current economic context. Advancements in the digital economy provide service enterprises with new digital technology support, leading to their reduced operational costs and heightened efficiency. Among them, artificial intelligence (AI) technology is highly praised by service enterprises. AI technology is extensively integrated into service enterprises' daily operations and management decision-making. However, limited research has been conducted on how AI technology can assist these enterprises in navigating external environmental disruptions. In response to management needs and bridge gaps in existing literature, this study focuses on "the influence of AI technology adoption on the organizational resilience of service enterprises."

Drawing insights from the literature review and deduction, this study assumed that AI technology adoption influences the organizational resilience of service enterprises and then performed an empirical analysis utilizing data from publicly listed service enterprises from 2010 to 2020. The results suggested that (1) AI technology adoption positively impacts the organizational resilience of service enterprises significantly; (2) AI technology adoption contributes significantly to enhancing both high liquidity and low-liquidity slack resources within service enterprises; (3) AI technology adoption positively influences the organizational

resilience of service enterprises through high-liquidity slack, which acts as a mediator; (4) The diversification strategy and scale of service enterprises play a negative role in adjusting the impact of AI technology adoption on high-liquidity slack resources. The empirical evidence confirms that AI technology adoption has a positive impact on the organizational resilience of service enterprises.

This study chose five typical service enterprises for case studies to delve deeper into the impact mechanism of AI technology adoption on the organizational resilience of service enterprises. It was observed that the response of the sample enterprises to the impact of COVID-19 unfolded across three stages, at each stage, AI technology adoption has played distinct roles in shaping organizational resilience. Specifically, it bolstered enterprises' environmental awareness and information judgment abilities in the pre-impact stage; facilitated algorithm innovation and intelligent decision-making during the impact stage; and assisted enterprises in exploring new paths and capitalizing on fresh entrepreneurial prospects in the post-impact stage. Additionally, the study employed two negative cases to validate the crucial role of AI technology adoption in enhancing the organizational resilience of service enterprises. Sub-study 2 conducted an in-depth comparative analysis. It reveals that service enterprises utilizing AI technology far outperform those that do not in nine fundamental operational capability indicators.

This study contributes to existing studies in the following ways: Firstly, it validates the impact mechanism of AI technology adoption on organizational resilience and reveals crucial antecedents of organizational resilience. Secondly, it sheds light on the effects of AI technology adoption on various slack resources within service enterprises and their marginal conditions. Finally, the study establishes a process model illustrating how AI technology adoption assists service enterprises in cultivating organizational resilience.

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1. Introduction

1.1 Research Background

Since the reform and opening up, particularly following China's accession to the WTO, Chinese enterprises have significantly engaged with the global economy and have assumed a vital role on the international stage. But at the same time, they are facing a more complex external environment. Rapid and continuous changes in the external environment have overwhelmed Chinese enterprises. After 2010, China-US trade frictions continued. The European debt crisis in 2012, the Russia-Ukraine confrontation in 2014, the Federal Reserve's interest rate hike in 2015, the European refugee crisis in 2016, and the COVID-19 pandemic in 2020 all had varying degrees of impact on the normal operations of Chinese enterprises. For the tertiary industry or service industry, the impact of the external environment has a greater impact on the operation of organizations. Services are generally more reliant on consumer demand stimulated by the external economic and social environment compared to manufacturing. How service organizations can sustain stability amid fluctuating environments and even thrive during crises has become a significant research focus within the current economic context.

Organizational resilience, as a manifestation of resilience in the realm of management, has garnered significant interest from both practitioners and academics, amidst the volatile environment in recent years (Bustinza et al., 2019; Duchek, 2020; He et al., 2022; P. Li & Zhu, 2021; P. Li & L. Sun, 2021; Shan et al., 2021; Song et al., 2021). The significance of resilience in challenging environments is evident. The concept of resilience is widely used in psychology, engineering, and ecology. In the field of psychology, the American Psychological Association (APA) defines psychological resilience as the process of adapting well in the face of life adversity, trauma, tragedy, threat, or other significant sources of stress. In the field of engineering, Pimm defined engineering resilience as the speed with which a system returns to its original shape after being disturbed in 1984. The faster the recovery speed is, the greater its resilience will be. In ecology, ecological resilience is defined as the tolerance to external disturbance under the premise of maintaining key thresholds, i.e. “resistance and adaptive capacity” (Adger, 2003). In recent years, the concept of resilience has been integrated into the field of management. Organizational resilience specifically pertains to how a company navigates external shocks, and preserves the stability of its core functions and operations in a fluctuating external environment, thereby leading to reduced financial losses and faster organizational recovery at the performance level (Ortiz-de-Mandojana & Bansal, 2016). Lothar Herrmann, President and CEO of Siemens Greater China, said at the 2020 Industry Forum of Siemens that during the COVID-19 pandemic, enterprises were faced with challenges such as supply chain and business stability. In VUCA (volatile, uncertain, complex, and ambiguous) environments, resilient enterprises can overcome the dilemma caused by external shocks and maintain their operation and development. What kind of enterprise exhibits greater organizational resilience? How can an enterprise cultivate organizational resilience? Addressing the aforementioned problems theoretically can assist Chinese service enterprises in developing organizational resilience in practical terms and effectively navigating future external environmental impacts.

Digital technologies have dramatically changed the current business environment and are exerting a profound influence on ongoing business operations (Acemoglu & Restrepo, 2019; Nambisan et al., 2019). In 2020, the release of GPT-3 by AI giant OpenAI drew worldwide attention. Using neural networks and machine learning, GPT-3 can generate interview questions, provide answers to scientific inquiries, and summarize book chapters with straightforward text inputs. Digital technologies, represented by AI, have disruptive effects on all walks of life (Baabdullah et al., 2021). The advancement of AI technology, encompassing deep learning and machine learning, empowers the processing of expansive unstructured datasets. The resulting data insights can offer valuable reference for enterprise behaviors and decision-making processes. AI technology has an impact on the automation, connectivity, customization, quality control, and innovation of enterprises. At the automation level, AI technology can reduce labor costs and improve production efficiency by automating various business processes. In terms of connectivity, AI can effectively integrate diverse business segments within an enterprise, facilitating real-time data exchange among them and consequently enhancing productivity. Regarding customization, AI technology can help enterprises quickly provide customized products and gain competitive advantages by rapidly identifying the real-time needs of customers. Concerning quality control, AI can diminish defects in services and processes while enhancing product and service quality through real-time monitoring of and feedback on enterprise business operations. For innovation, AI technology can assist enterprises in attaining a deeper understanding of the market, accelerating the development of new processes and products more efficiently, and ultimately securing long-term sustainable competitive advantages in the market. At present, the global AI market is expanding. According to a 2019 Deloitte report (see Figure 1.1), the AI market was estimated to reach USD 3.04 trillion in 2021 and USD 3.5 trillion in 2022. By 2025, the global AI market is expected to reach USD 6.4 trillion.

Evidently, the AI market is growing rapidly.

Digital and intelligent technologies offer great potential for the development of China’s service industry, affecting all business processes during its development. The emergence of AI technology can provide higher efficiency, productivity, and profitability for service enterprises, as well as personalized, convenient, and rich experiences for customers (Souto, 2015). Digital transformation is the primary productive force that drives the sustained high-quality growth of the service industry. The rapid iterative development of digital technology exerts a systematic and strategic influence on the service sector.

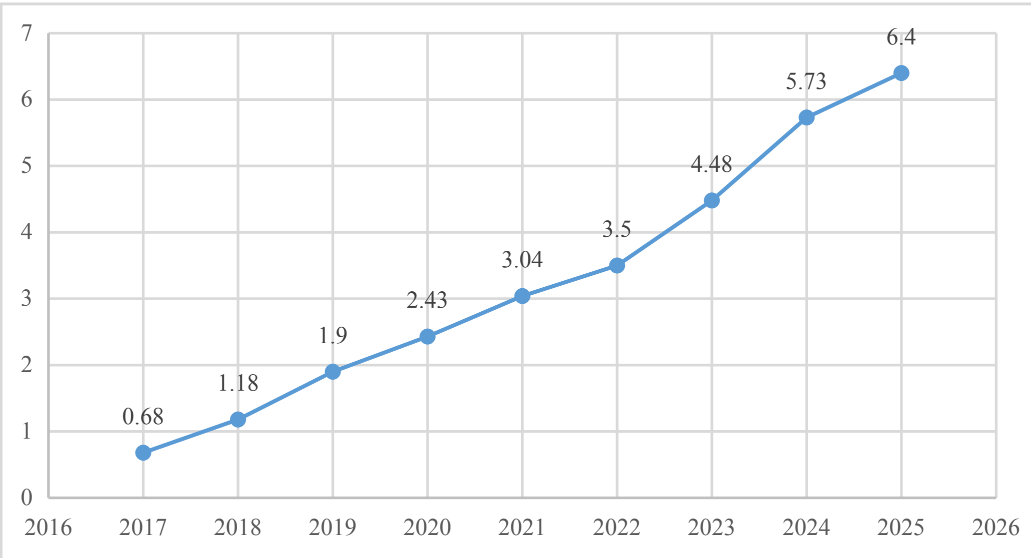

Figure 1.1 Global AI Market Scale (Source: Deloitte, Meta Sophia Research Institute)

Under the drive of data, computing power, and algorithms, combined with various technological means of data fusion and data processing, it guides consumer demands, efficiently matches supply, reduces transaction costs, and significantly boosts service productivity and efficiency. It creates a series of platforms based on data, forms a digital ecosystem, and facilitates smoother connections between the supply and demand sides to achieve dynamic balance at a higher level. It also improves resource allocation efficiency, promotes connectivity in various links of the value chain, reshapes the innovation chain, industry chain, and value chain, and collectively focuses on meeting deep-rooted, unsatisfied customer demands, including desires for authenticity, expectations for transparency and flexibility, appreciation of feedback loops, and desires for simplified interactions and payments, thus leading the innovation and development of the service industry.

In summary of current research findings, **AI technology adoption not only benefits the operation and growth of enterprises but also plays a crucial role in enhancing their organizational resilience amidst rapidly changing external environments.** Firstly, AI technology adoption enables enterprises to quickly capture, absorb, and process massive external information, allowing them to evaluate external market opportunities and potential crises. Secondly, the automation and connectivity of AI technology empower enterprises to digest market information from the external fluctuating environment more quickly, efficiently, and with higher quality, leading to a timely understanding of the environment and industry landscape. Thirdly, AI technology can provide practical insights for enterprises in applications, enhancing the reliability of their decision-making processes.

Based on the analysis of practical and theoretical backgrounds, this study creatively focuses on the formation process and marginal conditions of organizational resilience of service enterprises. The goal is to meet the needs of Chinese service enterprises to better address external environmental shocks. In addition, it explores the impact of AI technology adoption on organizational resilience in the context of digital transformation.

1.2 Research Question and Objectives

In the context of the above research background, this study proposed the research question: **How can AI technology adoption improve the organizational resilience of service enterprises?** Specifically, this study would delve deeper and rely on the following three sub-research questions to fulfill the research objectives:

(1) How does AI technology adoption affect the organizational resilience of service enterprises?

(2) What marginal conditions influence the relationship between AI technology adoption and the organizational resilience of service enterprises?

(3) In the context of specific shocks (e.g. COVID-19), what is the mechanism by which AI technology adoption affects the organizational resilience of service enterprises?

Firstly, this study focuses on whether AI technology adoption will impact the organizational resilience of service enterprises. Is the effect positive or negative? How does AI technology adoption affect the organizational resilience of service enterprises? Building on the previous inquiries, this study further investigates the marginal conditions that determine how AI technology adoption influences the organizational resilience of service enterprises. It emphasizes the organizational and individual characteristics that play a role in shaping the connection between AI technology adoption and the organizational resilience of service enterprises. Finally, this study aims to examine how service enterprises leverage AI technology to build organizational resilience in response to the challenges posed by COVID-19 between 2020 and 2022, using specific enterprise case studies.

This study will accomplish the following objectives.

(1) Exploring the impact of AI technology adoption on the organizational resilience of service enterprises

Service enterprises are more vulnerable to the impact of rapidly changing external environments. Investigating the formation mechanism of organizational resilience in service enterprises can enhance their capacity to sustain stability during external disruptions (DesJardine et al., 2019; Williams et al., 2017). This study aims to explore what factors affect the formation of organizational resilience in service enterprises. In an era where digital technology is prevalent in service enterprises, can AI technology enhance the organizational resilience of these businesses? In what ways can AI technology be used to foster the organizational resilience of service enterprises? This study initially examines the impact of AI technology, currently a focal point of interest, on the organizational resilience of service enterprises. Through empirical research, it delves into the direction and specific pathways through which AI technology adoption influences the organizational resilience of service enterprises.

(2) Examining the marginal conditions under which AI technology adoption affects the organizational resilience of service enterprises

The study will establish the influence model of AI technology adoption on the organizational resilience of service enterprises. On this basis, it will test the marginal conditions that determine how AI technology adoption impacts the organizational resilience of service enterprises. Specifically, this study examines two moderating variables in terms of organizational business level and enterprise scale. An organization's strategic choices shape the impact of AI technology. The extent of business diversification within an enterprise determines the direction and goals for employing specific technologies. Furthermore, the promotion of organizational resilience through AI technology adoption is also influenced by enterprise scale. The enterprise scale defines the scope and application scenarios for AI technology. Different-sized enterprises exhibit heterogeneous effects on enhancing organizational resilience through AI. Hence, it is essential to analyze the marginal conditions that determine how AI technology adoption can influence the organizational resilience of service enterprises, considering the enterprise scale.

(3) Summarizing the effectiveness mechanism of service enterprises in using AI technology to address the impact of COVID-19

Finally, this study concentrates on specific case studies of service enterprises. It summarizes, through multi-case analyses, how these enterprises leveraged AI technology to combat the repercussions of COVID-19 between 2020 and 2022. Specifically, this study centers on cases within the catering and hotel sectors, examining enterprises that sustained robust operations and growth amidst the challenges posed by COVID-19. The study highlights how these businesses apply AI technology to navigate the pandemic's effects across various operational processes.

1.3 Research Design

1.3.1 Research content

In the fluctuating external environment, the ability to uphold organizational resilience has emerged as a critical factor for the survival and sustainable growth of service enterprises. The development mechanism of organizational resilience has thus become a significant and widely discussed subject in academia and practical domains. Existing literature analyzes the antecedents of organizational resilience from the perspectives of organizational capability, organizational resources, and social networks. With the rapid development of digital technology represented by AI, scholars have discussed at different levels how AI can change the position of enterprises in the global value chains (GVCs) (Graetz & Michaels, 2018; Yang & Fan, 2020) and improve industrial structure transformation (Acemoglu & Restrepo, 2019; L. Li et al., 2021; Wang Yongqin & Dong, 2020), and also focused on the impact of AI technology on organizational structure, innovation, and decision-making (Agrawal et al., 2018). Can AI technology promote organizational resilience? What is the process and mechanism? What are the boundary conditions? At present, systematic analysis and answers are not available in relevant literature.

To answer the core research question—**How does AI technology adoption affect the organizational resilience of service enterprises**, this study comprises two research designs: Sub-study 1 is the empirical research concerning the impact of AI technology adoption on the AI technology adoption of service enterprises. Sub-study 2 focuses on case studies of how service enterprises enhance organizational resilience by leveraging AI technology in response to the challenges posed by the COVID-19 pandemic.

1.3.2 Research method

Research methods are vital for ensuring the quality of a study. Adopting scientific and reasonable research methods and technical routes can ensure the standardization of research and the scientificity of research conclusions. This study incorporates a range of research methods, including literature research, theoretical deduction, interviews, case studies, multiple linear regression, and the mediating effect test with adjustment. It also employs diverse data analysis software and tools like Stata and Mplus. Utilizing many research methods can enhance the stringency and standardization of this study. The two primary research designs mentioned earlier aim to combine case study and empirical research methods. This section will elaborate on the research methods used in this study.

(1) Literature research. The research leveraged the China Journal Full-text Database of Zhejiang University and Singapore Management University, alongside databases of Chinese and foreign journals including JSTOR, EBSCO, Elsevier, and Emerald. It conducted a thorough literature search using keywords such as AI, AI technology, and organizational resilience from CSSCI source journals and esteemed journals like AMR, AMJ, OS, ASQ, and JAP. The literature review focused on identifying theoretical junctions and gaps, delineating research topics, and enhancing our understanding of the current theoretical landscape.

(2) Theoretical deduction. The research topic of this study is intricately linked to the development of organizational resilience within enterprises, involving enterprise digital transformation, digital applications of service enterprises, and AI technology adoption. Thus, drawing insights from both theoretical and empirical research in organizational resilience, the study leveraged theoretical deduction methods to examine the potential effects of AI technology adoption on the organizational resilience of service enterprises.

(3) Second-hand data collection and interview. To gather data on organizational resilience and AI technology adoption in service enterprises, the study adheres to scientific methodologies and employs a mix of online and offline second-hand data sources (primarily leveraging the CSMAR database) to acquire the necessary empirical data. In addition, data collection and semi-structured interviews were conducted with five service enterprises that aligned with the

research requirements to obtain the text and data needed for case studies.

(4) Case study. The case study method was employed to delve into the challenges encountered by sample enterprises amidst COVID-19, and their strategic responses, and to formulate an effectiveness mechanism model for AI technology adoption on organizational resilience. Cross-case studies were conducted to compare how different service enterprises have applied AI technology at distinct stages of combating COVID-19 and analyze the role of AI technology across various operational modules.

(5) Empirical analysis. Based on forming empirical research hypotheses and research models, second-hand panel data were used for empirical data analysis. This study used STATA software for multiple regression analysis and MPLUS for the mediating effect test.

1.4 Research Significance

The study investigates the influence mechanism of AI technology adoption on the organizational resilience of service enterprises, examines the marginal conditions in which AI technology adoption impacts organizational resilience, and outlines the effectiveness mechanism of AI technology adoption in addressing the impact of COVID-19. By doing so, it contributes theoretically to existing research on organizational resilience and AI technology adoption. It also offers practical suggestions for enhancing the organizational resilience of service enterprises to tackle future environmental challenges.

(1) Theoretical significance

This study is expected to contribute to existing theories in two ways:

Contributing to antecedent and contextual research on organizational resilience: Exploring the factors that shape organizational resilience is a pivotal focus in studies on organizational resilience. Existing research focuses on the key antecedents of organizational resilience from the perspectives of organizational resources, organizational structure, organizational capability, organizational culture, and social networks. For the process mechanism of organizational resilience, it is proposed that an organization's cognitive and early warning capabilities before an external shock (Kahn et al., 2018), its responsiveness and resource allocation abilities during the shock, and its recovery (Ortiz-de-Mandojana & Bansal, 2016) and learning capacities (Linnenluecke, 2017) post-shock all play significant roles in determining whether it can sustain stable operations amidst the shock. In terms of organizational learning, the process mechanism of organizational resilience underscores the essential learning abilities of enterprises across three stages to address shocks. These abilities are intricately linked to the organization's ability for information acquisition. Previous studies have touched upon organizational characteristics linked to learning abilities. However, there has been limited focus on how the adoption of specific digital technologies during digital transformation influences the formation of organizational resilience. This study explores that AI is the key technology for enterprises to collect and process information.

By establishing an impact model of AI technology adoption on the formation of organizational resilience in service enterprises, this study identifies important antecedents of organizational resilience. Specifically, AI technology adoption is the core embodiment of organizational learning ability and dynamic ability. It helps enterprises identify possible external shock information in the pre-impact stage of facing external impacts. It allows for resource allocation based on rich information during the impact stage, quickly testing the effectiveness of enterprises' impact response decisions (Huang et al., 2018; Williams & Shepherd, 2016). After experiencing an impact, it enables organizations to gain adaptive abilities through further learning, assisting them in repositioning to capture market opportunities (Linnenluecke, 2017). In addition, the literature related to organizational theory reveals that variables such as enterprise scale characteristics play a significant role in enterprise performance at enterprises' strategic business level (Finkelstein & Hambrick, 1990; Hambrick & Mason, 1984; Norburn & Birley, 1988). Achieving organizational resilience is dependent on interactions with contextual variables. This study enriches the contextual research on the formation of organizational resilience by exploring the marginal conditions under which AI technology adoption affects organizational resilience.

Contributing to the research on the effectiveness mechanism of AI technology adoption: As a product of technological progress, AI embeds "intelligent manufacturing" in the production process and becomes an important force in promoting the "high-quality development" of the national economy. AI technology has played an important role in accelerating the reconstruction of global industry chains and promoting the transformation of industrial structures (Wang Yongqin & Dong, 2020; Zhou et al., 2022). For service enterprises, AI technology improves efficiency, productivity, and profitability, and provides customers with personalized, convenient, and rich experiences. From consumers' standpoint, intelligent customer service, precise information push, robot-assisted services, and other methods profoundly influence their needs, preferences, decision-making, and experiences (Ivanov & Webster, 2017). By modeling the relationship between AI technology adoption and the organizational resilience of service enterprises, this study enriches the understanding of how AI technology works in enterprises.

Existing research has focused on the role of AI technology in organizational structure, corporate innovation, and management decision-making (Levesque et al., 2022; Taddy, 2018). To cope with the rapidly changing external environment, an increasing number of service enterprises are using emerging digital technologies such as AI to search for and process internal and external information, thus improving their learning ability and dynamic ability to respond to external shocks. Existing theories lack an examination of the correlation between AI technology adoption and the formation of organizational resilience and have not clarified the marginal conditions under which AI technology is instrumental. From the perspective of organizational learning, this study focuses on the role of AI technology in service enterprises facing external shocks, explores the formation path of AI technology adoption to organizational resilience, and enriches the research on the effectiveness mechanism of AI technology.

(2) Practical significance

In addition, this study holds considerable practical significance. For enterprise development, the spread of COVID-19 constituted a disruptive and unexpected shock, often referred to as a “black swan” event. A black swan event refers to an extremely negative event or occurrence that is difficult to predict but may dramatically impact the operations of enterprises. Under the impact of COVID-19, China’s service enterprises faced direct challenges such as reduced operating income, increased pressure on operating costs, difficult capital turnover, low work resumption rate of employees, and great pressure on bank loans. Service enterprises lacking resilience successively closed down under the impact, and the industry encountered a major crisis. Exploring the influence mechanism of AI technology adoption on organizational resilience is crucial for enhancing the overall organizational resilience of service enterprises. It can assist these enterprises in sustaining their business operations amidst external shocks, while also seeking out new entrepreneurial opportunities and directions.

AI algorithms significantly enhance the ability of individuals and organizations to search for and spread information. This transformation has facilitated cross-disciplinary and cross-industry communication, fostering high-quality entrepreneurial opportunities with innovation. R. Wang (2022) noted that AI finds wider and more frequent application in China's tourism industry. An essential function of AI is to support the decision-making process (Agrawal et al., 2018). AI can sift through extensive datasets to identify common factors and, through meticulous analytical procedures, enhance the connection between theoretical frameworks and management practices. Uncertainty serves as a critical boundary condition in formulating decision-making theories. The technical solutions offered by AI mitigate this uncertainty (Alvarez & Barney, 2007). Therefore, in management practice, it is essential to use AI technology to assist management decision-making amid external shocks. Specifically, the findings of this study can help service enterprises better apply AI technology to integrate internal and external information and resources during COVID-19 to make decisions that stabilize organizational development and reduce losses. In the long run, the organizational dynamic abilities cultivated through the utilization of AI technology will aid service enterprises in being well-equipped to handle various external shocks and enhance their ability for sustainable development.

This study also provides some guidance for policy design. To harness the government's role as a promoter and regulator of AI technology effectively, the outcomes of this study will facilitate the government to elucidate how AI technology adoption contributes to cultivating the organizational resilience of enterprises. From a policy design perspective, it is imperative to establish an enterprise-university-research institution collaboration platform, enhance the commercialization environment for scientific research findings, and incentivize enterprises to boost R&D investments. For example, enterprises can be encouraged to engage in scientific research through policy tools like tax incentives, subsidies, and funding mechanisms. There also should be a focus on bolstering intellectual property rights protection and fostering an innovative environment. Additionally, scientific research institutions and enterprises should strengthen information and resource sharing to form close collaborative relations. Scientific research institutions possess substantial expertise in basic theory and key technologies, whereas enterprises excel in product R&D and marketing. They can leverage each other's strengths to expedite the commercialization and application of scientific and technological achievements by establishing joint R&D centers and collaborating on talent cultivation. Universities and research institutions can undertake targeted scientific research projects focused on AI technology transformation within service enterprises based on enterprises' technological and market needs.

2. Literature Review

2.1 Organizational Resilience

As an emerging economy, China experiences a growing economy within a progressively intricate and fluctuating environment. The external uncertainties and internal instabilities pose significant challenges to the stable development of Chinese enterprises. Organizational resilience refers to the core ability of an enterprise to quickly adjust and respond to crises in a complex and fluctuating environment. Under VUCA environments, both domestic and international landscapes are becoming more intricate, leading to a rise in unforeseeable events that potentially threaten enterprise growth. This threat can significantly impede the healthy and stable development of enterprises. For instance, challenges like global supply chain disruptions from the COVID-19 pandemic and the China-US trade war's decoupling trend pose serious risks to business stability. Consequently, the significance of enterprises' organizational resilience is more pronounced than ever. From the Chernobyl disaster and the "9/11 Incident" to events like the China-US trade war and the COVID-19 pandemic, the research focus on organizational resilience has continuously shifted (Linnenluecke, 2017). This topic remains a focal point of interest in both industry and academia, as it is vital for enterprises' survival and advancement. So, how can we understand organizational resilience? What are the factors influencing organizational resilience? How is organizational resilience measured? What are the affecting mechanism and effects of organizational resilience? The review covers the definition, measurement, influencing factors, affecting mechanism, and effects of organizational resilience, summarizing its theoretical framework and practical suggestions.

2.1.1 Definition and context of organizational resilience

Resilience is referenced in many disciplines, such as physics, engineering, psychology, and ecology. In the 1980s, management scholars introduced the concept of resilience to the field of management (Meyer, 1982; Staw et al., 1981) and applied it to various areas such as organizational learning, strategic management, and human resource management. They explored how enterprises can sustain stable development amidst rapidly changing external environments (DesJardine et al., 2019; Hillmann & Guenther, 2021; Iborra et al., 2020; Linnenluecke, 2017; Vogus & Sutcliffe, 2007; Williams et al., 2017). Some studies consider organizational resilience as both a trait and an outcome. For instance, Sahebjamnia et al. (2018) posited that an organization demonstrates resilience when it sustains its critical functions at or above the minimum business continuity target level throughout the maximum tolerable interruption period following any disruption. Wang Yong et al. elucidated organizational resilience as the state where enterprises react to contextual crises and challenges from a static standpoint, adjust to new environments, and uphold active adaptation. Some other studies consider organizational resilience as a process and ability. Ability refers to the organization's ability to sustain steady growth in the face of external shocks (Sajko et al., 2021), ensure ongoing operations (DesJardine et al., 2019), and recover from the shocks (Buyl et al., 2019; Vegt et al., 2015). The term "process" encompasses how an organization develops particular abilities to address adverse environmental factors during external shocks, how it proactively mitigates risks beforehand, how it responds during crises, and how it adapts for recovery post-crisis (Williams et al., 2017).

Table 2.1 Relevant Concepts and Connotations of Organizational Resilience

S/N	Author	Year	Concept and connotation
1	Wang Yong & Cai	2019	Organizational resilience is a state where enterprises react to contextual crises and challenges, adjust to new environments, and uphold active adaptation.
2	Sahebjamnia	2018	Organizational resilience is the ability of an organization to maintain the continuity of key operations and critical functions during disruptions.
3	Lengnick-Hall et al.	2005	Organizational resilience is a blend of enterprise-level cognition, behaviors, and contexts. It represents the ability of an enterprise to navigate current circumstances, as evident in its comprehension of the environment and the response strategies implemented.
4	Ma et al.	2018	Organizational resilience refers to an organization's ability to adapt, survive, and even thrive in the face of accidents and catastrophic events.
5	Hillman & Guenther	2021	**Organizational resilience is the ability of an organization to maintain functions and recover fast from adversity.**

While scholars may hold various viewpoints on the definition of organizational resilience, a fundamental aspect that remains consistent is the vital dimension of upholding stability within a tumultuous environment. Hillman and Guenther (2021) outlined that the fundamental aspect of organizational resilience is stability. They emphasized that a key demonstration of organizational resilience lies in preserving the normal functioning of core operations and minimizing performance fluctuations amid challenging circumstances (McCarthy et al., 2017). Building upon these ideas, **the study defines organizational resilience as an organization's ability to ensure the survival, recovery, and growth of enterprises in the face of external crises and challenges. Stability is identified as the primary defining characteristic of organizational resilience in this context.**

Organizational resilience is a context-sensitive concept influenced by shock events, showcasing fragmented characteristics in existing research. This paper describes the research context of organizational resilience in existing literature from two aspects: severity and knowability of shock events. Firstly, shock events are categorized into incremental and disruptive sub-dimensions by severity. Secondly, by knowability, shock events are classified into two sub-dimensions: expected and unexpected. Incremental and expected shock events can be likened to “gray rhino” events, representing high-probability risk events that are often inadequately addressed. These events exist in seemingly ordinary circumstances and are challenging to identify. However, over time, gray rhino events have the potential to pose an irreversible threat to the development of enterprises. Disruptive and unexpected shock events can be described as “black swan” events, denoting low-probability risk occurrences that are challenging to foresee. Such events are even harder to forecast and less probable than gray rhino events, akin to the “9/11 Incident,” presenting a potential danger to the ongoing operations of enterprises.

2.1.2 Measurement of organizational resilience

The concept of organizational resilience is intricate, and scholars have not yet established a definitive agreement on the approach to measure it. We summarized the measurement of organizational resilience from static and dynamic perspectives in the existing literature.

From a static view, scholars regard organizational resilience as a trait. Kantur et al. obtained first-hand data through questionnaires focusing on robustness, agility, and integrity (Kantur & İşeri-Say, 2012). DesJardine identified the measurement index of organizational resilience using second-hand data from two dimensions: loss severity and recovery time (DesJardine et al., 2019). Similarly, Ortiz-de-Mandojana (2016) used second-hand data to measure organizational resilience from three perspectives: financial volatility, sales growth, and survival rate.

From a dynamic perspective, scholars regard organizational resilience as a process. Patriarca et al., (2018) proposed that at the organizational level, resilience can be described as a combination of four cornerstones: monitoring, responding, learning, and anticipating. Focusing on the results of enterprise organizational resilience and investigating the effects of AI technology adoption on organizational resilience, this study takes a static perspective. It considers organizational resilience as a product of the challenging environment faced by the organization.

Hillmann et al. (2021) believe that stability is the most important feature of organizational resilience, and both organizational flexibility and stability are reflected in the stability of organizational performance. Therefore, **this study employs the stability of organizational performance as a metric for organizational resilience.**

Table 2.2 Measurements Related to Organizational Resilience

S/N	Author	Year	Dimension	Data
1	DesJardine	2019	Loss severity and recovery time	Second-hand data
2	Ortiz-de-Mandojana	2016	Financial volatility, sales growth, and survival rate	
5	Hillman & Guenther	2021	Stability of organizational performance	Second-hand data
3	Patriarca	2018	Monitor, react, predict, and learn	First-hand data
4	Kantur	2012	Robustness, agility, and integrity	

2.1.3 Factors shaping organizational resilience

(1) Organizational resources

Organizational slack can provide a buffer against external shocks to the organization. Bromiley (1991) defined slack resources as excess resources accessible to an organization during a given planning cycle. Slack resources, including slack funds (Linnenluecke, 2017; Williams et al., 2017), backup resources (Huang et al., 2018), and flexible resources (Ortiz-de-Mandojana & Bansal, 2016), operate as a "sandbag" to endure risks when enterprises encounter shocks. These resources provide enterprises with a cushion and the necessary time to adapt internally, allowing them to navigate challenging phases successfully. Meanwhile, scholars who have long been engaged in organizational resilience research also underscore the vital role of human resources in shaping organizational resilience (Lengnick-Hall et al., 2011; McCoy & Elwood, 2009). Lengnick-Hall conducted a conceptual review focusing on the cognitive dimension, behavioral dimension, and contextual dimension of human resources to explore their impact on enterprise resilience. From an organizational human resource management perspective, McCoy et al. delved into the influence of employee willingness and attitudes on the shaping and effectiveness of organizational resilience in the face of shocks.

(2) Organizational structure

The organizational structure plays a crucial role in shaping the formation and function of organizational capability. If organizational resources serve as the "sandbag" during times of external shocks, the organizational structure acts as the "fortress" safeguarding the enterprise. Analogous to architecture, it shields the organization from overwhelming external shocks. The organizational structure consists of multiple dimensions, including the centralization of organizational structure (Pugh et al., 1968). In studies concerning organizational resilience, decentralized organizations are considered to exhibit greater flexibility in responding to shocks and demonstrate faster information dissemination, more agile responses, and enhanced abilities for reaction and execution (Linnenluecke, 2017; Vegt et al., 2015). At the same time, some scholars have highlighted that organizations with a more centralized structure are better suited for risk identification and response (Nayal et al., 2020). In a word, an effective organizational structure enhances information flow, resource allocation capabilities, and decision-making prowess within the organization during times of shocks, thereby ensuring stable operations amidst disruptions.

(3) Organizational capability

In the literature related to organizational resilience, organizational capabilities, including organizational learning ability, dynamic ability, and creative ability, are also regarded as important influencing factors of organizational resilience (Lengnick-Hall et al., 2011; Ma et al., 2018). The organizational learning ability can facilitate an organization in adapting to external shocks and significantly influence the establishment and evolution of organizational resilience (Knight, 2000; Robb, 2000). From a process perspective, the abilities of organizational awareness, utilization, and reconfiguration play a significant role in developing organizational resilience (Teece et al., 1997). Meanwhile, the creative and resourceful initiatives of management can aid organizations in responding and adapting flexibly (Williams & Shepherd, 2016), thereby exerting a positive influence on organizational resilience.

(4) Organizational culture

In the research on organizational resilience, organizational culture is recognized as a significant driver that influences organizational resilience. Cortu (2002) suggested that organizational culture enables organizations to reinterpret environmental information and assign specific meanings to it. Employees perceive themselves as a community of shared interests existing alongside the organization, which is deemed crucial in a fluctuating environment. During times of shock, organizational culture can reshape employees' perceptions, mitigate panic and negative cognition, and uphold organizational stability (Sutcliffe, 2003; Weik, 2009).

(5) Social network

From the perspective of external influencing factors, social capital and social relations play an important role in shaping organizational resilience. Kahan posited that organizations are embedded within external social networks and internal member relationships, and positive social relations can facilitate a quicker return to normal operations for an organization (Kahan et al., 2009). After analyzing the impact of the "9/11 Incident" on airlines, Gittell discovered that social relations significantly influence organizational resilience. Positive social relations can effectively anticipate shock events and offer financial resources crucial for organizational recovery, thereby enhancing organizational performance in the face of shock events (Gittell et al., 2006).

2.1.4 Process mechanism of organizational resilience

The process mechanism through which organizational resilience operates is dynamic (Ma et al., 2018). An organization's cognitive and early warning abilities before an external shock (Kahn et al., 2018), its responsiveness and resource allocation abilities during the shock, and its recovery (Ortiz-de-Mandojana & Bansal, 2016) and learning abilities (Linnenluecke, 2017) post-shock all play significant roles in determining whether it can sustain stable operations amidst the disruption.

In the first stage, i.e. pre-impact stage, organizational perception plays a crucial role in organizational resilience performance. This perception is determined by the organization's ability to acquire information, its well-established management processes, flexible organizational structure, and decision-making mechanisms. In addition, advancements in information technology have significantly improved organizations' proficiency in information retrieval, processing, and decision-making responsiveness (Bustinza et al., 2019; Hu et al., 2021; Shan et al., 2021). Meanwhile, the position and status of an organization in social networks have a certain impact on its information acquisition before the shock. Moreover, the forward-thinking nature of enterprises at the strategic level is a crucial factor in determining whether enterprises can perceive impacts effectively.

In the second stage, when an organization is undergoing shocks, its ability to adapt and adjust is the most critical ability during this stage. Several factors enable an organization to respond quickly and adjust flexibly: the number of slack resources (Gao et al., 2017), the ability to allocate resources (Huang et al., 2018), effective information sources and strong processing capabilities (Linnenluecke, 2017; Sajko et al., 2021; Williams et al., 2017), and the creative and resourceful activities undertaken by management (Williams & Shepherd, 2016). For example, after the outbreak of COVID-19, enterprises promptly adopted diversified business strategies to enlarge the pool of shared resources among enterprises and reach cross-industry cooperation with other enterprises. This approach has assisted organizations in quickly recovering from the pandemic, ensuring the stability of organizational structures and performance. However, it is crucial to highlight that creative behavior must strike a balance between organizational flexibility and stability (Sajko et al., 2021) within the strategic framework of an enterprise (Williams & Shepherd, 2016, p. 2) to realize organizational resilience.

In the third stage, following the organization's encounter with a shock, the core demonstrations of organizational resilience lie in learning ability and dynamic ability, encapsulated in two categories: incremental enhancement and path breakthrough. In the dimension of incremental enhancement, Linnenluecke (2017) emphasized learning in shock to acquire adaptability. In the dimension of path breakthrough, Bothello highlighted the repositioning of the organizational path after adversity (Bothello & Salles-Djelic, 2018), while Gao emphasized the ability to seize and leverage new opportunities following adversity (Gao et al., 2017).

2.1.5 Effects of organizational resilience

The current debate surrounding the financial performance of organizational resilience mainly focuses on key dimensions: survival, volatility, and recovery (DesJardine et al., 2019; Sajko et al., 2021). Volatility and recovery reflect the anti-fragility ability of an organization in the face of crisis, while survival is the ultimate goal of organizational resilience (Gao et al., 2017). In general, organizational resilience can help enterprises maintain stability and recover from shocks in the face of environmental fluctuations (Linnenluecke, 2017), and achieve survival and growth (Gao et al., 2017; Ortiz-de-Mandojana & Bansal, 2016). To sum up, possessing high organizational resilience is beneficial for organizations to progress from "survival" to "flourishing" to "sustained success."

Meanwhile, relevant literature indicates that the impact of organizational resilience can be categorized into short-term and long-term effects (P. Li & Zhu, 2021). The long-term effect of organizational resilience pertains to organizational growth, while the short-term effect focuses on organizational survival. For short-term survival, enterprises necessitate short-term decisions and business adjustments, whereas long-term growth demands superior strategic direction and enduring investments. Due to limited resources and attention, enterprises must strike a balance between these two matters, leading to a paradox (Zhou & Park, 2020). Balancing the long-term and short-term effects of enterprise organizational resilience is crucial, as they are interdependent and indispensable.

With the deepening of research on organizational resilience, the discussion around organizational resilience is expanding. At present, most studies are mainly based on conceptual discussion and theoretical deduction (Burnard & Bhamra, 2011; Duchek, 2020; Linnenluecke, 2017; Vogus & Sutcliffe, 2007). They lack quantitative research grounded in actual financial data of enterprises (Vegt et al., 2015; Williams et al., 2017). At the same time, the existing literature has rich conceptual discussions on the antecedents and processes of organizational resilience, identifying the antecedents such as slack resources, organizational capabilities, and social networks. However, there remains a scarcity of relevant empirical research.

In the digital era, the impact of digital technology on organizational resilience in a fluctuating environment is also a crucial topic of interest for both practitioners and academia (Verreynne et al., 2018). At present, the impact of digital technology on organizational resilience is extensively debated in the literature, examining perspectives such as enterprise innovation (Shan et al., 2021), enterprise entrepreneurship orientation (Hu et al., 2021), and management leadership (Zhao Sijia et al., 2021). As a crucial technological advancement, AI technology has a significant impact on organizational management and business logic. There is a noticeable absence of discourse on how AI technology influences organizational resilience in existing studies, with the impact process remaining vague. This study initiates the discussion on AI technology adoption and utilizes the organizational learning perspective to investigate the effects of AI technology adoption on organizational resilience.

Furthermore, existing studies on organizational resilience also neglect to discuss its contextual conditions. Literature in organization theory highlights that enterprise features play a crucial role in enterprise performance (Ansoff, 1957, 1958; Finkelstein & Hambrick, 1990; Norburn & Birley, 1988). Organizational resilience is intertwined with interactions with variables associated with business strategy and enterprise features. Current research restricts the comprehension of contextual variables shaped by organizational resilience. Hence, the boundary conditions for the development of organizational resilience in VUCA environments require further exploration, to gain a more precise and detailed understanding of the organizational resilience formation process. Does AI technology adoption affect the formation of organizational resilience? Through what mechanisms will the impact of AI technology adoption be realized? Is the effectiveness of AI technology adoption on organizational resilience influenced by marginal conditions such as enterprise feature variables? These questions need urgent responses.

2.2 AI Technology Adoption

2.2.1 AI system

Digital technology is changing the nature and scope of business activities, with one notable aspect of digitalization being the capability to automate tasks that demand substantial human involvement and labor (Nambisan, 2017). Recent advancements in AI technology empower machines to analyze extensive unstructured datasets through complex adaptive algorithms, carrying out activities that traditionally necessitate human intelligence (Choudhury et al., 2018; Stone et al., 2016). AI technology, as a significant technological revolution in human history, has deeply influenced the behaviors of various participants, including individuals, enterprises, and countries. AI technology may not just enable cost and productivity enhancements but also usher in a fundamental innovation in organizational management and business logic (Amabile, 2019; Cockburn et al., 2018).

Existing literature defines AI as a system's ability to correctly interpret external data, learn from such data, and achieve specific goals and tasks through flexibility (Haenletin & Kaplan, 2019). AI encompasses a wide variety of activities and concepts, including the use of multiple software and algorithms to support or perform tasks that previously required human cognitive abilities. AI embodies a form of systemic intelligence that absorbs human knowledge through machine reading and computer vision, leveraging this information to automate and speed up tasks typically executed by humans (Li Xiaohua & J. Li, 2022). Many experts view the creation of AI technology as a solution to some of the most intricate challenges in human existence. However, AI is an ever-evolving phenomenon, solely displaying technological innovations that demonstrate comparable cognitive abilities to humans. AI remains an ambiguous concept for different technological innovations that are vital to humanity (Poola, 2017). This new technology, with a profound impact on human society, will be dissected from the connotations of AI systems.

AI consists of three core elements: domain structure, data generation, and general-purpose machine learning (Taddy, 2018). They can also be colloquially understood as data, algorithms, and computing power (Nambisan, 2017). Firstly, AI needs to be integrated into a particular domain structure. Domain structure refers to expertise in engineering tasks. At present, AI can solely be commercialized within industries featuring clear domain structures like chessboards and video games. Domain requirements dictate that businesses must possess specialized expertise in technology application, and refine and consolidate this knowledge via structural econometrics to establish a data structure compatible with AI systems. Subsequently, the data is processed utilizing relaxation and heuristic methods. Secondly, AI needs the support of data generation. Data generation refers to the enormous amount of data used to train AI systems and the tools that generate the data needed to support algorithmic learning. The quantity and quality of data determine the extent of algorithm training and optimization, serving as the key factor in gaining competitive advantages for enterprises implementing AI technology. Well-established enterprises rooted in the traditional Internet hold huge data assets and distinct advantages over small startups. However, acquiring initial data does not guarantee that enterprises will obtain sustainable competitive advantages. Enterprises also need to acquire more dynamic data for algorithm iteration. Therefore, on the development path, enterprises should focus on meeting product demands and establishing internal cloud systems to facilitate data storage and generation. Startups often face more disadvantages in utilizing AI technology (Chalmers, 2021). Finally, AI systems should employ machine learning to discern patterns within unstructured data and forecast future trends. General-purpose machine learning is an important foundation for AI technology adoption in enterprises. A general-purpose algorithm means that the algorithm can adapt to more complex scenarios without requiring extensive adjustments to transfer the algorithms accumulated by an enterprise in one niche field to another. The current development of the AI sector mainly benefits from the development of deep neural networks, which can quickly discover rules from text, audio, and video data, and greatly improve the efficiency of automatic processing compared with previous algorithms. Currently, AI based on deep learning algorithms is like a black box because the intermediate processes through which managers get output results from specific inputs are uncontrollable. Existing AI systems remain weak (X. Sun et al. 2020), i.e., AI abilities are limited to specific domains, exhibiting a significant gap from achieving artificial general intelligence (AGI). Therefore, solely relying on AI technological advancements makes it challenging to address intricate issues within the complex society. In future theories and practice, more focus should be placed on refining product forms based on application scenario needs to drive advancements in AI technology.

AI finds application in such sectors as transportation, human-robot interaction, service-oriented robots, health care, education, and public safety. In the transportation domain, there are high expectations from the public regarding the reliability and safety of AI systems. Self-driving vehicles, supported by AI technology, point the way forward (Russell, 2015). The AI dynamic approach will leverage limited resources in the transportation domain, providing data availability and extensive connectivity (Li et al., 2018). Similarly, AI technology can simulate the communication and coordination between humans and machines by virtually connecting them (Kannan et al., 2019). Today, the Internet of Things (IoT) and cloud-based systems devices are more and more widely used in the social and economic dimensions of AI. In addition, object recognition, robotics, and data-driven product platforms are proliferating (Kannan et al., 2019; Russell et al., 2015). Compared with other digital technologies, AI technology has a greater impact on the economy and society. These practical changes have brought new opportunities and challenges to organizational management research. The following part will summarize research on the influence of AI technology across three spheres: industrial development, organizational management, and entrepreneurial action.

2.2.2 AI technology and industrial development

(1) Global value chain

As the latest advancement in science and technology, AI has enhanced both the efficiency of technology and the customization of production, and its contribution to enhancing productivity is well acknowledged by scholars domestically and internationally (Graetz & Michaels, 2018; Yang & Fan, 2020). The advancing AI technology is accelerating the restructuring of GVCs. Beyond its general technical characteristics, AI is prominently capital-biased, influencing not only the factor utilization structures at the microeconomic level within enterprises but also altering the patterns of international trade division at the macroeconomic level (Lawson, 2010). Corporate production activities involve separate stages, including R&D, design, manufacturing, transportation, sales, and after-sales services, which can be performed by companies in-house or outsourced for global production (Porter, 1985). In the process of labor division in GVCs, enhancing technological capabilities and reducing factor costs emerge as the primary strategy for facilitating a nation’s GVC advancement (Gallagher & Shafaeddin, 2010). Based on this, Azadegan & Wagner (2011) differentiated between general and exploratory technological advancements, with the latter being the key to propelling a country’s GVC advancement. AI technology, as a seminal technological revolution, signifies a profound upgrade within the GVCs, catalyzing a substantial shift in production modes and patterns of labor division.

Scholars integrated AI technology adoption into the theoretical analytical framework of economics. They undertook exploratory studies on achieving equilibrium in economic growth within the context of AI technology adoption, how AI technology advancements alter factor earnings, and whether it leads to unfairness (Acemoglu & Restrepo, 2018; Aghion et al., 2017). Liu Bin & Pan (2020) and Lyu et al. (2020) utilized data from the International Federation of Robotics (IFR) to examine the effects of advancements in intelligent and automation technologies on the labor division within GVCs. They identified the primary influence mechanisms as enhancing competitiveness, reducing trade costs, spurring technological innovation, and refining resource allocation abilities. Using a multi-country, multi-stage GVC competition model, He et al. (2021) investigated China's responses to the challenges posed by AI technology and its involvement in GVC competition amidst the latest wave of scientific and technological revolution. Their findings indicate that within the GVC labor division framework, China is predominantly integrated into the downstream stages of the GVCs, whereas the United States primarily occupies the upstream stages. Furthermore, by contrasting scenarios without AI technology adoption against those with such adoption, it is discovered that the shift toward capital substitution for labor driven by AI technology adoption leads to markedly disparate impacts across countries. Within the GVC labor division, AI technology adoption erodes the traditional labor division advantage that developing countries leverage cheap labor power for integration into the GVCs. Meanwhile, developed countries capitalize on AI technology to advance the substitution of capital for labor, thereby diminishing labor costs, fostering industrial reshoring, and amplifying their existing advantages within the GVC labor division. Zhou et al. (2022) demonstrated that AI contributes to enhancing a country's position in the GVC labor division by improving productivity, optimizing the quality of industry products, and impacting labor input (job replacement or creation). Arising from technological advancements, AI incorporates intelligent manufacturing into the production workflow, thereby becoming a significant driver of high-quality development of the national economy (Wang Yongqin & Dong, 2020). On the one hand, intelligent technologies, exemplified by robots, can raise the efficiency of production processes, standardize production norms, and enhance product stability and precision, thereby augmenting product quality. Meanwhile, robots typically necessitate higher-quality inputs compared to non-automated machinery, demanding an increased proportion of advanced production factors. The interplay of these high-quality elements heightens production efficiency and yields superior end products. Recent research by DeStefano and Timmis (2021) confirms that robots do help improve product quality. On the other hand, stringent quality standards frequently serve as a prerequisite for integration into GVCs. Enhanced product quality bolsters the competitiveness of various economic entities. This outcome facilitates a country's broader and more profound engagement in the GVC labor division across existing production stages (DeStefano & Timmis, 2021). It also effectively incentivizes the distribution of subsequent production stages in regions with higher value-addition and fosters upward mobility toward the higher end of value chains, thus ultimately helping surmount the "low-end lock-in" challenge and leading to high-quality development (Zheng & Zheng, 2020).

The existing research on AI technology and GVCs reveals the significant disparities in technological capabilities and factor endowments among countries, shaping their varied stances on AI technology. Some countries face constraints on adopting AI technology due to a misalignment between the AI technology and their existing factor endowment structures. This circumstance may escalate the development imbalance between developing and developed countries regarding their participation in GVCs. While developing countries may find themselves at a competitive disadvantage regarding AI technology adoption, they may enhance their position in GVCs by improving overall productivity, ensuring better industrial product quality, and fostering job creation through AI technology.

(2) Transformation of industrial structure

AI, as general technology with attributes of new infrastructure, may exhibit biased substitutability in terms of either labor or capital. On the one hand, AI adoption in production is mainly realized through robots. Robots and manpower each play distinct roles in production, possessing unique advantages (Wang Yongqin & Dong, 2020). Robots are primarily tasked with performing repetitive and low-tech tasks, supplanting manpower in certain processes, effectively reducing production costs, and enabling mechanization and automation in production. This technological adoption has been associated with enhancements in production efficiency (Acemoglu & Restrepo, 2019). On the other hand, robots, as a form of capital investment, not only deliver immediate production benefits but also facilitate long-term capital accumulation. They help deepen technological progress and advance machine productivity within existing automated tasks, contributing to sustained productivity growth over time (Acemoglu & Restrepo, 2018a; L. Li et al., 2021). As a strategic technology in the new wave of scientific and technological innovation, AI is poised to reshape the existing industrial landscape and drive its transformation and upgrading in several ways.

Firstly, AI technology possesses the spillover characteristic of infrastructure. General technologies refer to foundational and widely used technologies that influence every sector of the economy; examples include steam technology, electrical power, and information technology driving three industrial revolutions, respectively. AI is regarded as the emblematic general technology of the Fourth Industrial Revolution, or Industry 4.0 (Agrawal et al., 2019; Guo, 2022). Despite AI technology being market-driven in its adoption, its infrastructure-like spillover characteristic necessitates governmental investment and development. The 2018 Central Economic Work Conference in China emphasized the importance of enhancing the development of new infrastructure such as AI, the Industrial Internet, and the IoT. As a novel form of infrastructure, AI has altered the landscape of existing industrial infrastructure.

Secondly, AI is poised to revolutionize traditional modes of production, yet it may exhibit a biased substitutability effect toward either labor or capital. Existing literature describes AI from two main perspectives. The first perspective perceives AI as a production factor-augmenting technology—this could be in the form of capital augmenting (Graetz & Michaels, 2018; Nordhaus, 2015; Sachs & Kotlikoff, 2012) or labor augmenting (Bessen, 2018). For both capital- and labor-augmenting technologies, the relative substitutability of AI for labor or capital hinges upon the elasticity of substitution. As such, this perspective does not necessarily suggest a greater tendency for AI to substitute labor or capital. The second perspective views AI as an enabler of automated production, which makes it more likely to substitute labor (Acemoglu & Restrepo, 2018). However, AI-driven automation may only replace a portion of the labor force. AI can serve as a supportive tool that enhances labor productivity and spurs demand for specific types of labor, such as jobs that are difficult to automate, demand robust digital information skills, and need AI's auxiliary function. Consequently, the implications of AI on the demand for labor are mainly embodied as structural changes and do not inevitably signal a reduction in the overall labor demand (Acemoglu & Restrepo, 2019; Bryn-jolfsson et al., 2018; Korinek & Stiglitz, 2017).

Thirdly, the potential for AI to be applied varies across industries, so the emergence of new business forms and patterns driven by AI will facilitate the transformation and upgrading of industrial structures. Fueled by fresh theories and technologies such as mobile Internet, big data, supercomputing, sensor networks, and brain science, existing AI exhibits novel characteristics like deep learning, cross-border integration, human-machine coordination, group intelligence sharing, and autonomous control. The unique production methods of different industries will integrate with these characteristics to varying degrees, which leads to differentiated impacts across sectors. One circumstantial evidence is that an AI patent is typically applied to a specific industry. For instance, 15% of current patent filings refer to communication and transportation, 12% to life and medical sciences, and 11% to personal services, computers, or human-computer interaction. Other industries involving patent application include banking, entertainment, security, manufacturing, and the Internet. Analysis suggests that in labor- and capital-intensive manufacturing sectors, AI reduces labor dependency and enables low-cost customization. In contrast, in technology-leading and market-changing industries, AI is pivotal for enhancing R&D efficiency and for precisely predicting and responding to market dynamics. Specifically, AI holds considerable, differing prospects in industries such as digital government, finance, healthcare, automobile, retail, and high-end manufacturing. Research by Cheng et al. (2019) examining companies and employees in China indicates substantial variance in robot application across industries: The greater the scale of employment and the higher the capital-labor ratio, the more extensive the application of robots. R. Wang (2022) noted that AI finds wider and more frequent application in China's tourism industry. The following section will examine the impacts of AI technology on the development of the tourism industry.

(3) Development of service industry

Digital and intelligent technologies unlock considerable opportunities for the development of the service industry, with implications for all business processes throughout industrial development (Souto, 2015). Take the cultural tourism industry as an example: Existing research centers on the impacts of AI technology adoption on the industry's development.

Big data and AI equip cultural tourism enterprises with enhanced efficiency, productivity, and profitability while offering customers personalized, convenient, and enriching experiences (Samara et al., 2020). Viewing from the supply side in the cultural tourism industry, AI is evolving from weak to strong forms, affecting employment, service processes, costs, and management methods (Baggio & Cooper, 2013). From the tourists' and customers' standpoint, features such as intelligent customer service, targeted information delivery, and robotic sensing services substantially influence consumer needs, preferences, decision-making, and experiences (Ivanov & Webster, 2017). Wei Xiang (2022) pointed out that the digital economy stimulates innovation in tourism-related big data, smart tourism, and tourism blockchain through interactive virtual-real iterations, optimal allocation of resources, and transcending value boundaries. Xia et al. (2022)

considered that digital empowerment enhances the efficiency of cultural tourism resource discovery, protection, and promotion, improving consumer experiences, activating the potential for integrated development of culture and tourism, and promoting its high-quality growth.

Digital technologies enable the informatization, networking, digitization, and intellectualization of the cultural tourism industry through penetration, reorganization, and leadership. This drives the industry’s digital transformation. “Penetration” signifies that digital technology gradually integrates into various sectors and organizations of the cultural tourism industry. The full-spectrum digitization of the innovation chain, industry chain, and value chain exemplifies the essence of digital empowerment. Data function as a production factor. The in-depth application of the new-generation technology cluster including 5G and AI has facilitated transformative changes across the entire cultural tourism industry. Shifts in the cooperation models among the upstream and downstream segments of the cultural tourism industry chain have been observed. Investment in and development of digital economy infrastructure, represented by ICT, have spurred innovation in tourism and reshaped the relationship between producers and consumers within the industry. Furthermore, the digital economy fosters the growth of the cultural tourism industry by enhancing total factor productivity, refining the industrial structure, and facilitating the sharing of economic benefits. At the macro level, digital transformation forms the technological bedrock for the development of the cultural tourism industry and catalyzes an increase in tourism demand. At the micro level, digital technology forges and sustains sound relationships between the cultural tourism industry and its consumers by delivering premium services, thus contributing to improving tourist satisfaction.

In terms of “reorganization,” the integration of information and communications technology across all stages of the customer journey has driven the convergence and reorganization of both physical and virtual components. That gives rise to novel tourism experiences and, consequently, a wealth of new business forms, patterns, and growth points, facilitating the reorganization of various factors. Major manifestations include the following: (1) The emergence of online tourism shopping: Mobile tourism applications have become crucial tools. Based on historical data, search records, and personal information, tourism systems proactively offer suitable travel options even before customers perceive them, allowing for online transactions; (2) Omni-channel model in the cultural tourism industry: The industry is no longer dependent on a single supplier; instead, it thrives on multi-party cooperation. The omni-channel sales model broadens the potential for businesses; (3) Personalized customer experiences: Enhanced data gathering and analytics capability enable consumers to receive personalized services and access tailored experiences. Successful cultural tourism enterprises are mainly distinguished by unique customer preference-related designs and highly personalized services; (4) The expansion of the sharing economy: Digital technology and platforms facilitate the sharing, convergence, and integration of resources and information. Technologies like widespread high-speed Internet, search and geolocation, mobile payment, and social media platforms have spurred the rapid expansion of the sharing economy.

Regarding “leadership,” digital transformation is the primary productive force that drives the sustained high-quality growth of the tourism industry. The rapid iteration and advancement of digital technology exert a systematic and strategic influence on the tourism industry. Under the drive of data, computing power, and algorithms, based on data fusion and processing, the combination with various technological means guides consumer demands, efficiently and dynamically matches supplies, reduces transaction costs, and significantly boosts productivity and efficiency within the tourism industry. This approach creates a series of data-based platforms, forms a digital ecosystem, facilitates smoother connections between the supply and demand sides, and achieves a dynamic balance at a higher level. It also improves resource allocation efficiency, promotes connectivity in various links of the value chain, and reshapes the innovation chain, industry chain, and value chain. Meanwhile, business is conducted with a collective focus on meeting deep-rooted, unsatisfied customer demands, including desires for authenticity, expectations for transparency and flexibility, appreciation feedback loops, and desires for simplified interactions and payments, thus leading the innovation-based development of the tourism industry.

2.2.3 AI technology and organizational management

In the field of organizational management research, scholars have found that AI technology influences organizational structure, organizational innovation, and management decisions.

(1) Organizational structure

While AI technology does not fundamentally revolutionize organizational structures (Brock & Wangenheim, 2019), it exerts a significant influence on both the labor division and enterprise boundaries. In limited empirical research on AI's impacts on organizational structure, Davenport and Ronanki (2018) found that the labor division of routine tasks (such as tax-loss harvesting or tax-saving investment options in the context of financial advisory) becomes more automated. Conversely, tasks that deliver high value and require customer interaction continue to be implemented by human workers. This finding aligns with the theory proposed by Huang and Rust (2018) regarding the four intelligence types (mechanical, analytical, intuitive, and empathetic) required for service tasks. The theory suggests that as technology progresses, the distribution of tasks within a company will shift. In their opinion, AI will initially augment tasks through mechanical and analytical intelligence, and then develop intuitive and empathetic intelligence potentially substituting all types of work. Raisch & Krakowski (2021), however, underlined that the balance between automation and augmentation is not straightforward, and the contradictions and interdependence between these two aspects must be examined to achieve the most productive results for an enterprise.

The opinions on AI's effects on employment vary among scholars. The "substitution theory" posits that robots, which are primarily tasked with repetitive, low-skilled jobs, assume roles formerly undertaken by human labor, thus potentially displacing low-skilled workers and causing unemployment (Graetz & Michaels, 2018; Kong et al., 2020). The "creation theory" contends that AI utilization spurs economic growth and creates new tasks, while human workers have a comparative advantage in tackling new and more complex tasks, which could lead to increased labor demands (Acemoglu & Restrepo, 2018). Although these two perspectives are a matter of debate, scholars are converging on the understanding that both effects will inevitably transform the content of production tasks and the labor force. The ultimate overall effect is determined by the interplay of both effects mentioned before. Relevant research suggests that routine positions in the middle level, productive workers, managers, and low-skilled laborers are more susceptible to being replaced (Graetz & Michaels, 2018; L. Li et al., 2021). The replacement of human labor with robots undoubtedly reduces the meaningless loss of production costs. Simultaneously, the integration of robots accentuates the need for specific skills in the workforce and creates demand for job roles that complement them, such as managers, technical scientists, or non-production workers. The increased employment of these highly skilled positions fosters the advancement of human capital (Bonfiglioli et al., 2020; Meltzer, 2018).

The demand for data and computational power required for training AI algorithms spurs the convergence of software and hardware within the same enterprise. In other words, enterprises need to upload big data to cloud platforms or leverage chip integration algorithms to realize the cycle of data, computational power, and algorithms. The software-hardware integration within an enterprise broadens its scope and increases the complexity of its internal management. To manage this increased complexity, enterprises need to streamline certain business segments, thus narrowing their scope. Conversely, the domain knowledge needed for product development calls for integrating specialists from diverse domains, warranting an expansion of scope (Li Xiaohua & J. Li, 2022). Although some job categories may shrink or disappear, many entrepreneurial organizations' structures will be reshaped around AI systems, with new tasks and work roles serving the new engine. This will lead to more skilled, self-employed individuals handling high-paying outsourced jobs (Aghion et al., 2017). As Davenport & Ronanki (2018) observed, no all the benefits of this technology will be realized by incorporating AI into existing processes, since many businesses are experimenting with the technology (Brock & Wangenheim, 2019). It is therefore foreseeable that as AI technology sees broader application, new organizational structures will be fostered (Chalmers et al., 2021).

(2) Enterprise innovation

Within an organization, innovation is seen as a function or activity that brings forth new products, services, or processes, providing short-term or long-term value for the innovating entities (Truong & Papagiannidis, 2022). Several models have been used to elucidate the comprehension and implementation of innovation within an enterprise. Still, the innovation process typically comprises four stages: the discovery and generation of fresh ideas, screening of ideas, experimentation of ideas, and development and commercialization of ultimately selected ideas (Kijkuit & Ende, 2007; Mariello, 2007). Each stage is extensively associated with the distinct human capability to devise creative solutions to emerging challenges (Amabile, 2020). From a technical standpoint, AI possesses the vast potential to substitute for or enhance human abilities across a broad spectrum of activities including those associated with innovation. However, the current status of AI development indicates that it is typically used in specific tasks in narrowly defined fields that call for substantial human planning (Cockburn et al., 2018). This implies that the likelihood of AI substituting human workers in creative tasks during the innovation process is presently low. Viewed from a different angle, AI sees its competence in handling and learning from vast data, as well as its proficiency in classifying, clustering, and predicting tasks on a large scale. It suggests that it could assist humans with cognitively intensive support tasks that are less reliant on extensive subjective judgment. In light of the significant growth in data and information accessible to innovators, AI may assist in processing this vast data, potentially reducing the resource cost associated with these tasks (Haefner et al., 2021).

The new idea discovery and generation stage entails pinpointing significant yet unresolved issues that can be addressed with innovative solutions. This stage is often considered vague, as innovators need to navigate through a vast search space, frequently involving the processing of copious amounts of unstructured data such as text, images, or videos (Kakatkar et al., 2020). AI algorithms, with their capacity to analyze and synthesize voluminous unstructured data, can aid innovators in broadening their search space (Muhlroth & Grottke, 2020), thereby facilitating the exploration of more ideas (Haefner et al., 2021). Although AI is not expected to replace human judgment in selecting meaningful ideas, it can help innovators with their search tasks. By structuring data, it allows ideas to emerge from the interpretation of results. Some ideas might not be recognizable to innovators due to time and resource constraints. For instance, in the pharmaceutical industry, the search for potential proteins may be so extensive that even a large research team cannot address it (Yang et al., 2019). Similarly, in the consumer goods industry, innovators might harness AI to autonomously search online forums to identify and classify key topics and needs.

During the screening stage, the focus is placed on evaluating the ideas and selecting the most innovative ones for further development (Kudrowitz & Wallace, 2013). Innovators can use machine learning to explore external data and score ideas based on predictions using a set of input parameters. Scores may vary with the weighting of parameters, so innovators can adjust the weighting according to their objectives. For instance, the scoring of ideas will vary if the emphasis is placed more heavily on future revenue rather than on the product novelty. The impact of AI is likely to be related to the number of ideas to be selected and the complexity of the selection criteria.

Testing ideas is often based on a sample of innovators facing targeted customer groups to collect feedback (Sawhney et al., 2005). With access to extensive customer data, innovative companies can harness AI to predict an idea's value according to certain objectives (projected earnings, market compatibility, or consumer acceptance). In manufacturing, AI can assist in selecting the most promising materials for testing. For example, the machine learning method is employed to analyze the optimal combination of materials based on the characteristics of new products (Haefner et al., 2021). For online platforms or products, problem-solving learning loops help innovators gather real-time information about specific new functions (Verganti et al., 2020), such as customer responses to newly designed interfaces. Because such loops are automated, innovators can experiment with more functions, without the need to design an experiment for each function. In scientific domains such as chemistry, it is proposed that specialized AI technology can deliver forecasts with a high degree of correlation to real-world physical outcomes (Wallach et al., 2015).

Finally, once an idea has passed the testing and validation, it progresses to the product development stage, in which it is transformed into a commercialized product in the marketplace. This stage is intensely solution-focused, confronting more specific decisions like selecting functions and design shape or color (Verganti et al., 2020). With machine learning and deep learning analyzing historical consumer choices, innovators can obtain prior preferences regarding certain functions. In addition, machine learning can be used to predict material combinations aligning with predefined technical standards or production costs, according to the combination of technical data from a manufacturer's previous production and manufacturing processes and external data sources. At this stage, the value of using AI is likely to lie in helping innovators with secondary (e.g. choosing a particular function) or narrowly defined decisions (e.g. predefined technical attributes). At the commercialization stage, AI clustering ability can help identify target customer groups and automate mail activities. Some AI-powered platforms provide automated solutions for sending large volumes of personalized emails to boost response rates.

Emerging technologies have ushered in new production and trade relationships, whilst posing conflicts and challenges to users, enterprises, governments, and other stakeholders (Liang et al., 2020). Companies have to invest considerable manpower in introducing to users the issues that AI technology can address and the value it delivers. Even when customers are willing to embrace a specific product, enterprises might face a lengthy product validation period often extending to one or two years, which heightens the validation expenses for startups. At the same time, public anticipation of AI offerings has increased, driven by media overhype surrounding the technology's potential value. Presently, AI-related basic algorithms are immature, and the performance of AI-based products often falls short of public expectations, which leads to confusion about AI technology among enterprises, users, and the public. Developing AI products necessitates understanding a specific scenario (Taddy, 2018). This challenge is caused by the limitations of machine learning algorithms which typically process data structures in set formats. As a result, it is necessary to manually integrate information such as needs, problems, and operation processes in scenarios into structured knowledge. Therefore, enterprises face the challenge of how to more efficiently assimilate scenario-related knowledge to enhance their technological edge and market expansion abilities. Future research might delve into the competitive advantages and their realization paths of different market actors, including traditional enterprises, incumbent enterprises, and start-ups, in the evolving landscape of AI technology.

(3) Management decision-making

The rise of AI technology influences not only corporate practices but also diminishes the uncertainty in management decision-making processes, thereby raising the demands on the decision-making ability and acumen of top management teams (Levesque et al., 2022). Scholars give special focus to the integration of AI-driven decision-making into enterprise structures (Raisch & Krakowski, 2022). Shrestha et al. (2019) proposed achievable configurations: full human-to-AI delegation (typically for automated fraud detection or advertising recommendation); hybrid—human-to-AI and AI-to-human—sequential decision-making (e.g. for recruitment or health monitoring); and aggregated human-AI decision making (e.g. using AI as an independent check and balance against decisions other members of the board of directors). Entrepreneurial companies may find particular interest in the AI-human sequence decision-making model that is employed to refine open innovation strategies and identify and select creative ideas.

An essential function of AI is to support the decision-making process (Agrawal et al., 2018). AI can sift through extensive datasets to identify common factors and, through meticulous analytical procedures, enhance the connection between theoretical frameworks and management practices. Uncertainty serves as a critical boundary condition in formulating decision-making theories. The technical solutions offered by AI mitigate this uncertainty (Alvarez & Barney, 2007), presenting challenges to established theories. AI has transformed the interaction between entities and their surroundings, especially entrepreneurial behaviors within uncertain environments. AI discovers “patterns” by analyzing vast data, thus enabling predictive outcomes. Enhanced precision in predictions significantly diminishes uncertainty (Agrawal et al., 2018). This evolution poses challenges to existing decision-making theories while creating more opportunities for developing new theories. For instance, some scholars propose that AI can effectively lessen the uncertainty associated with patterns. It means that machine learning can resolve rule-based problems, thereby reducing the uncertainty entrepreneurs face during opportunity recognition (Townsend & Hunt, 2019). Future research can delve into the impacts of changes in uncertainty on exploring entrepreneurial opportunities, enterprise growth, entrepreneurial strategy, and entrepreneurial performance.

Using big data to evaluate strategic choices has become common among start-ups. However, AI-driven decision-making differs from the widely used data-driven approaches. The latter involves applications that summarize complex data to form an input application for some form of human judgment. In contrast, AI can make automated decisions and suggested actions based on all available data, removing biases inherent to judgment, and needing to aggregate data to make it comprehensible to humans (Colson, 2019). Agrawal et al. (2017) argued, accordingly, that while the cost of this prediction will fall, **human judgment as the other input to decision-making will become more valuable**. Given their capacity to process and integrate vast volumes of unstructured data, AI algorithms can aid innovators in broadening their search scope (Muhlroth & Grottke, 2020), thereby enabling the exploration of more ideas (Haefner et al., 2021). Although AI is not expected to replace human judgment in selecting meaningful ideas, it can help innovators with their search tasks. By structuring data, it allows ideas to emerge from the interpretation of results. Some ideas might not be recognizable to innovators due to time and resource constraints.

AI-assisted decision-making poses a greater challenge to management decision-making. Enterprise decision-making in practice is complex. Merely leveraging AI algorithm-based decision-making is insufficient for achieving sustainable competitive advantages in the face of a constantly evolving external environment. For instance, AI algorithms tailored to specific sectors and business strata can yield an excess of dynamic data. Handling and synthesizing this data hinges on the experience and judgment ability of decision-makers. Members of top management teams focusing on specific business might not possess the required proficiency to integrate data from intricate sources. Consequently, applying AI technology in organizational decision-making raises the bar for management teams.

2.2.4 AI technology and entrepreneurship

Reviewing the research on organizational management through AI, it is observable that AI technology adoption poses a challenge to the organizational structures and norms of seasoned enterprises. A common strategy among many large enterprises is to delegate AI technology adoption and AI system management to technology-based start-ups (Chalmers et al., 2021). The management requirements resulting from AI technology progress and the pursuit of mastering cutting-edge technologies have prompted many AI technology-focused start-ups to infiltrate various industries, to compete with large enterprises through advanced technologies. These start-ups often rely on foundational technology developed by universities and research institutions, and commercialize the technology through enterprise-university-research institution cooperation. Start-ups like iFLYTEK and AISpeech are dedicated to the commercialization of AI technology. Scholars have also noticed the impact of AI technology on entrepreneurship.

Cockburn et al. (2018) argued that AI marks an attempt to develop a new innovation "playbook" that leverages large data sets and learning algorithms to engage in precise prediction. As such, it is reasonable to assume that these **data sets and algorithms can be utilized in identifying and exploring entrepreneurial opportunities**. The novelty of these AI systems for innovative search processes lies in their capacity to discern patterns or nuances within data that may elude human detection. In a medical science context, this might involve applications that can recognize cancer at an earlier stage than human experts (Leachman & Merlino, 2017; Miller & Brown, 2018). Such superhuman capabilities for information search and prediction are leveraged across various business contexts. For example, real estate firm Skyline2 amasses millions of data points about property trends, including yield levels and default rates, to forecast optimal locations for investor purchases. Likewise, Scoop Markets analyzes Twitter feeds to anticipate breaking news that may impact exchange prices, thus enabling stock and cryptocurrency traders to act ahead of market fluctuations.

Given the heterogeneity of startups in form, function, and purpose, existing research has identified three ways in which entrepreneurs may use AI to enhance information search and idea generation. Regarding the first method, a niche cohort of science and technology-centric start-ups is poised to use AI to unearth technological solutions in complex combinatorial problem space (Agrawal et al., 2019). Deep learning's proficiency in uncovering intricate patterns within high-dimensional data has been proved, which makes it applicable in many fields, including science, business, and government. This method resonates with existing theories that address entrepreneurial traits (Shane, 2000; Venkataraman, 2000). In the process of identifying entrepreneurial opportunities, there is typically an objective “thing” (such as a material, molecule, or genetic sequence) representing an opportunity in the market that requires a substantial amount of experimentation to uncover. AI, with its computational capabilities, offers the potential to conduct such experiments at a relatively low cost, thereby aiding in the recognition and discovery of latent opportunities. The second method involves analyzing social media and other online content by using social sentiment analysis (Gaspar et al., 2016) and natural language processing to identify customer needs. Entrepreneurs, for instance, can browse online consumer forums for product or service categories they expect to revolutionize, to explore untapped demands. Alternatively, they may monitor broader technological trends on social platforms (Davidsson et al., 2018), for counterintuitive or nascent insights that provide favorable information asymmetries. While these processes can be performed manually, AI-enhanced methods can largely identify demand or market imbalances (Kirzner, 1979), and amalgamate disparate knowledge fragments to spark new insights that propel business development. Additionally, start-ups have the potential to capitalize on AI systems for hypothesis testing or to utilize their accumulated data assets in forecasting customer responses to alterations in functions or prices. The current entrepreneurial approach highlights customer engagement as a means to obtain ideas and verification hypotheses. Though useful, these methods are prone to various biases, such as recall bias or social acceptability bias. Incorporating machine learning into these processes may diminish search costs and mitigate the risks of failures related to time-consuming product or service development.

AI algorithms significantly enhance the ability of individuals and organizations to search for and spread information. This transformation has facilitated cross-disciplinary and cross-industry communication, fostering high-quality entrepreneurial opportunities with innovation. The impact of AI on uncertainty boundaries has altered the traditional opportunity identification process (Shane & Venkataraman, 2000). For example, identifying entrepreneurial opportunities is an imaginative decision-making process, and successfully matching information in innovative ways is a key ability of excellent entrepreneurs (Ardichvili et al., 2003). AI enhances decision-making efficiency, minimizing the need for entrepreneurs to pinpoint opportunities and diminishing the impact of their information-matching skills in the startup process. From an empowerment perspective, AI aids entrepreneurs in extracting rules and patterns from vast data via machine learning. It facilitates the identification of entrepreneurial opportunities and enhances the decision-making efficiency of entrepreneurs facing multiple opportunities. Specifically, experiments serve as an effective method for entrepreneurs to verify their ideas (Kerr et al., 2014). AI eliminates some low-quality ideas in advance through simulation, shortening the process of verifying ideas through experiments and accelerating the entrepreneurial process. Moreover, AI influences the utilization and exploitation of entrepreneurial opportunities by impacting factors like the innovation and perception of founders and their entrepreneurial teams.

2.3 Slack Resources

Organizational slack resources are an important antecedent of organizational resilience, acting as a buffer during times of external impact. To delve deeper into the impact of AI technology adoption on the creation of organizational slack resources and organizational resilience, the following section will review the definition, classification, and influence of slack resources. This will lay the groundwork for discussing the correlation between the liquidity of slack resources and organizational resilience.

2.3.1 Definition of slack resources

Organizational slack, as one of the core concepts in organizational theory, has attracted much attention from academia. Penrose (1959) believed that surplus resources exist within enterprises, and the complete equilibrium state between demand and supply is unattainable. She argued that enterprises need these surplus resources for their growth and should emphasize surplus resource utilization. According to the analysis of enterprise resource theory, some special resources bring enterprises sustainable competitive advantages. As one of the core concepts of organizational theory, "organizational slack resource" has attracted important attention from academia and become a new topic in the study of resource-based view (RBV). Barney (1991) stated that slack resources play a role in uncovering the connection between enterprise resources and sustainable competitive advantage as well as the essence of the connection. Moreover, a key role of the resources an enterprise possesses is to assist in mitigating risks and capitalizing on opportunities within the environment. Cyert and March (1963) first introduced the concept of organizational slack as "an excess of resources between what the firm possesses and what is required to maintain its current state." The existence of slack resources can "provide individuals and groups within the organization with a sense of satisfaction." Later scholars expanded the concept based on this definition. For example, Child (1972) proposed from the perspective of management strategy that organizational slack is a surplus (performance above a satisfactory level). It enables the organization's management to adopt structural arrangements at its discretion. The study adopts the widely accepted definition by Bromiley (1991), which defines slack resources as surplus resources stored by an organization within a set planning period.

2.3.2 Classification of slack resources

Currently, slack resources are commonly classified in four ways. According to their manifestation, they are categorized as financial slack, human slack, and technical slack (Meyer, 1982). They can also be classified based on their availability as available slack, recoverable slack, and potential slack (Cheng & Kesner, 1997). In terms of stability, they fall into absorbed slack and unabsorbed slack categories (Singh, 1986). From a management flexibility perspective, they can be grouped as high-liquidity slack and low-liquidity slack (Sharfman et al., 1988). Some scholars also classify slack resources based on research needs and various dimensions, such as flexibility and scarcity of such resources (Gee et al., 1997; Voss et al., 2008). George (2005) argued that within an enterprise, two types of slack resources exist concurrently, with high-liquidity slack offering greater management flexibility and strategic options compared to low-liquidity slack.

Other researchers divide slack resources into three categories. For example, Bromiley (1991), Cheng and Kesner (1997), and Palmer and Wiseman (1999) classified slack resources based on their availability, from high to low, as high-flexibility slack resources, low-flexibility slack resources, and potential slack resources. Accessible slack resources refer to slack resources that are currently not engaged in specific tasks and can be readily utilized to support enterprise creativity. The nature and impact of such slack are akin to high-flexibility slack. Recoverable slack resources refer to slack resources that have already been integrated into the enterprise’s cost structure or allocated to other tasks, existing as additional costs. Recoverable slack resources cannot be immediately utilized, and their nature and impact are similar to low-flexibility slack. Potential slack refers to an organization's capacity to acquire additional resources from the external environment, such as obtaining more debt or equity capital (Bourgeois & Singh, 1983). The key difference between potential slack resources and other resources lies in the fact that using potential slack resources signifies more future costs. The examples include interest payments due to liabilities and the impact on the company's image among investors caused by altering potential slack. Therefore, managers only utilize, transform, or reuse potential slack after careful consideration or in crucial and urgent circumstances (Geigner & Cashen, 2002).

2.3.3 Slack resources and performance

The theories used in research on the relationship between slack resources and enterprise performance are mainly divided into two categories. One is organizational theories, such as the Behavioral Theory of the Firm (Cyert & March, 1963) and the Resource-based View (Barney, 1991). The other is economic theories, such as Resource Constraint Theory (Baker & Nelson, 2005; George, 2005), and the Agency Theory (Jensen & Meckling, 1976). Scholars have extensively researched the relationship between slack resources and organizational performance. Their studies have revealed various types of relationships, including positive or negative linear ones and non-linear ones such as U-shaped, inverted U-shaped, and S-shaped. However, a consensus on the matter has not yet been reached (Davis & Stout, 1992; Greenley & Oktemgil, 1998).

(1) Direct effect

Positive correlation. Some scholars observed that resource slack can stimulate innovation and risk-taking behavior, providing enterprises with the opportunity to explore new projects and ultimately enhance enterprise performance (Singh, 1986; Su et al., 2009). Other scholars focused on the crisis from environmental changes, discovering that resource slack can help shield enterprises from the impact of turbulent environments, thereby contributing to sustained enterprise performance (George, 2005). In exploring specific dimensions of resource slack, Miller and Leiblein (1996) found that only recoverable slack positively influences the financial performance of enterprises, while other types of resource slack show no significant effects. Conversely, W. Li & C. Liu (2012) discovered that both unabsorbed and absorbed slack can enhance the financial performance of enterprises.

Negative correlation. Resource slack surpasses the minimum input for achieving the established production level, which leads to an increase in the costs of enterprises and a decrease in their financial performance (Cheng & Kesner, 1997). Furthermore, some scholars find that resource slack might breed overconfidence among managers, fostering complacency with the existing state of affairs. This may slow down enterprises' responsiveness to the market, potentially exerting a negative impact on enterprise performance (Davis & Stout, 1992; Zona, 2012).

Positive U-shaped relationship. Certain scholars discover that resource slack benefits enterprise innovation only when it surpasses a certain threshold. Insufficient resource slack not only has a limited impact on enterprise innovation but also diminishes the utilization efficiency of resources. Consequently, a positive U-shaped relationship exists between resource slack and enterprise performance (Bromiley, 1991; Li Xiaoxiang & C. Liu, 2011).

Inverted U-shaped relationship. In contrast to the above perspective, some other scholars observed an inverted U-shaped relationship between resource slack and enterprise performance. Specifically, lower levels of resource slack can foster enterprise innovation and positively influence enterprise performance. Conversely, when resource slack becomes excessive, effective resource utilization becomes challenging, which leads to a decline in enterprise performance (Herold et al., 2006; Nohria & Gulati, 1996; Tan & Peng, 2003).

Transposed S-shaped relationship. Drawing from the perspectives of both positive and inverted U-shaped relationships, some scholars conclude that insufficient resource slack proves wasteful for enterprises. An appropriate level of resource slack can enhance enterprise performance, while resource slack exceeding a certain threshold once again becomes wasteful. As a result, a transposed S-shaped relationship exists between resource slack and enterprise performance (Jiang & Zhao Shuming, 2004).

(2) Indirect effect

Extensive research indicates that the influence of resource slack on enterprise performance occurs through mediating variables, mainly including technological innovation and diversification strategy.

Technological innovation. A higher level of resource slack necessitates enterprises to frequently seek opportunities for utilizing these idle resources. While helping them find market or technological opportunities arising from environmental changes, it provides sufficient flexibility for enterprises to swiftly respond to the opportunities (Herold et al., 2006; Lee, 2015). In addition, it ensures that enterprises possess adequate resources and capabilities to pursue innovation and avoid missing opportunities due to overcaution and indecisiveness. Therefore, resource slack can foster enterprise innovation and subsequently enhance enterprise performance (Malen & Vaaler, 2017; Marlin & Geiger, 2015).

Diversification strategy. On the one hand, enterprises need additional slack resources to implement the diversification strategy. On the other hand, enterprises that possess a large number of resource slack tend to adopt the diversification strategy as a way to enhance resource allocation efficiency (Hughes et al., 2015; Natividad, 2013). Furthermore, the adoption of the strategy by an enterprise necessitates the reallocation of certain resources. A greater degree of resource slack can lessen the potential resistance an enterprise might face during the strategy implementation process (Liu Bing et al., 2011; Tan & Peng, 2003).

(3) Regulating effect

Resource slack impacts enterprise performance, both directly and indirectly, and influences the relationship between other variables and enterprise performance. For instance, Moreno et al. (2009) discovered that resource slack enhances the positive effect of organizational learning on quality management. W. Li and Li Xiaoxiang (2011) observed that resource slack can mitigate the adverse effects of emergencies on enterprise performance. Furthermore, Y. Li (2016) identified that resource slack amplifies the contribution of breakthrough innovation to enterprise performance. Lee and Wu (2016) found that resource slack moderates the relationship between R&D investment and enterprise performance.

In summary, resource slack can have both positive and negative effects on enterprise performance; the extent of these effects varies across different contexts, leading to diverse overall impacts (Chiu & Liaw, 2009). When the benefit is the primary concern for an enterprise, the flexibility afforded by resource slack is crucial in navigating environmental shifts and internal pressures. Resource slack can enhance enterprise performance by encouraging innovation and risk-taking behavior. When efficiency is the primary concern for an enterprise, resource slack manifests as increased operational costs, negatively impacting enterprise performance. Hence, the impact of resource slack may differ between short-term financial performance and long-term growth performance, necessitating a clear distinction.

As previously mentioned, there is considerable variance in the observed relationship between resource slack and enterprise performance across different studies. Such variance is likely affected by contextual factors. The types of relationships between resource slack and enterprise performance depend on the context (Bradley et al., 2011; Vanacker et al., 2013). Existing research primarily focuses on contextual factors such as environmental, industrial, and organizational ones.

Environmental factors. Existing studies suggest that environmental dynamics can amplify the positive relationship between resource slack and both enterprise innovation and performance. For example, M. Li (2016) discovered that environmental dynamics bolsters the contribution of financial slack to technological innovation; Wang Yani and Cheng (2014) found a positive U-shaped correlation between absorbed slack and enterprise performance, which is intensified by environmental dynamics.

Industrial factors. Existing research indicates that the relationship between resource slack and enterprise performance is influenced by factors such as industry type, the intensity of competition, and the industry life cycle. For example, W. Li and C. Liu (2011) found that in industries with more intense competition, unabsorbed slack has a larger positive impact on enterprise performance, while absorbed slack tends to have a larger negative impact on enterprise performance.

Organizational factors. Existing research has sparingly examined the moderating role of organizational factors in the relationship between resource slack and enterprise performance. Further scholarly attention is thus needed in this regard. Resource slack increases enterprises' operating costs, and its value can be fully realized only through adept management. Hence, factors such as an organization's agency structure, resource management capabilities, risk preference, and strategic tendency are likely to substantially affect the value of resource slack.

In long-term research, scholars typically focus on that different types of slack resources may impact enterprise performance differently, while overlooking the possibility that various classification standards for slack resources and their effects on enterprise performance may vary according to industry-specific characteristics (Sharfman et al., 1988). In the context of China's economic transition, the relationship between slack resources and enterprise performance may present additional complexities (Tan & Peng, 2003). Nohria and Gulati (1996) observed that Chinese enterprises, particularly state-owned enterprises, are frequently perceived as having an excess of slack resources that lead to diminished performance. This attitude fosters a generally negative perception of slack resources. However, there is a lack of empirical research specifically investigating this issue. The research of Tan & Peng (2003) within the context of China's economic transition affirmed and expanded upon the findings by Nohria & Gulati (1996). The research revealed that unabsorbed slack resources are positively related to enterprise performance, whereas absorbed ones are negatively related to enterprise performance. This indicates that the conclusions of organizational theory are more applicable to unabsorbed slack resources, whereas the conclusions of the principal-agent theory are more applicable to absorbed slack resources. Furthermore, the authors also validated a non-linear, inverted U-shaped relationship between slack and performance. The relationship signifies the existence of an optimal range of organizational slack, with slack below or above this optimal range having adverse impacts on performance.

Many scholars have discovered that the positive or negative impact of slack on business activities like innovation is not determined by the slack resources themselves, but by an enterprise's internal or external environment. Does the impact of slack resources on enterprises hinge on certain internal or external factors? Geiger and Makri (2006) confirmed that the intensity of R&D serves as a moderating factor in the relationship between slack resources and innovation. Their research suggests that available slack facilitates enterprise innovation, while the positive correlation between potentially exploitable slack and the innovation process remains unverified. In other words, varying types of slack have different effects on different innovation behaviors of enterprises. This is particularly true for high-tech enterprises, where the prudent management of slack resources greatly benefits the pursuit and development of high-risk ventures. Furthermore, enterprise resource allocation plays a regulating role in the association between slack and environmental responsiveness. When organizations allocate more resources to enhance the efficacy of external markets (prospector strategy), an increase in slack resources evidently bolsters their responsiveness to the environment. When they allocate more resources to enhance internal efficiency (defender strategy), an increase in slack resources ostensibly diminishes their responsiveness to the environment (Cheng & Kesner, 1997). These two studies examined slack resources from the perspectives of internal R&D and strategic factors within enterprises. So what is the influence of their external factors? Herold et al. (2006) expanded the findings of Nohria and Gulati (1996), examining the link between organizations' unabsorbed slack resources and patent-based innovation. Their study uncovered an inverted U-shaped relationship between unabsorbed slack resources in organizations and the significance of enterprise innovation. This relationship is influenced by industries' propensity to patent. Specifically, for enterprises in industries dependent on patents for competitive advantage, slack resources positively impact innovation. In contrast, for those in industries not dependent on patents for competitive advantage, organizational slack negatively impacts innovation.

Moreover, a body of researchers represented by Tan and Peng (2003) initiated an exploration into the role of slack resources in the context of transition economy. Given the current state of China's transition economy, there is a significant presence of slack resources within its enterprises, especially in the service sector. Consequently, discussing organizational slack is extremely relevant for transition economies like China, as highlighted by Ju et al. (2009), Peng et al. (2009), and Su et al. (2009). In the context of transition economy, the mechanism of action of slack resources for enterprises is different from that in the West (Tan & Peng, 2003). Research in this domain is nascent, with a primary focus on slack and performance. By incorporating moderating variables such as environment or enterprise nature, the research background of economic transition is enriched and highlighted. Owing to its recent development, this field often references findings from Western studies. Nevertheless, it encounters challenges similar to those mentioned above. The investigation depth of slack is insufficient, which signals a need for greater research efforts in the future.

2.3.4 Slack resources and organizational resilience

Almost all studies on slack resources believe that slack resources help enterprises mitigate the impact of changes in the external environment. The prevailing consensus within the literature is that slack resources play a positive role in the context of sudden crises. Firstly, slack resources can buffer and absorb environmental fluctuations and reduce the negative impact of external risks. For example, Reuer and Leiblein (2000) found that slack resources are negatively correlated with enterprise risks, which means that slack resources can reduce enterprise risks. Secondly, slack resources support enterprise managers in making decisions flexibly and rapidly. For example, some studies found that the availability of slack resources empowers enterprise employees and departments to make decisions independently. In this way, managers can reduce their decision-making pressure due to the independent decision-making of employees or departments and power decentralization. So they can devote more energy and time to making decisions more efficiently and responding quickly to external threats. Thirdly, slack resources help identify and exploit opportunities to support enterprise reforms. Enterprises with more slack resources can carry out more projects leveraging external opportunities and then obtain more returns. Conversely, those with limited slack resources have to reduce costs and cut expenditures, thus missing potential opportunities.

Organizational slack resources are an important antecedent of organizational resilience, acting as a buffer during times of external impact. Bromiley (1991) defined slack resources as excess resources accessible to an organization during a given planning cycle. Slack resources, including slack funds (Linnenluecke, 2017;

Williams et al., 2017), backup resources (Huang et al., 2018), and flexible resources (Ortiz-de-Mandojana & Bansal, 2016), operate as a “sandbag” to endure risks when enterprises encounter shocks. These resources provide enterprises with a cushion and the necessary time to adapt internally, allowing them to navigate challenging phases successfully.

The existing literature on organizational resilience has not considered the influence of digital technology in exploring **the antecedents and influence mechanisms** of organizational resilience. It is thus of great significance to explore the influence direction and mechanism of specific digital technologies.

The existing literature on AI technology adoption has discussed the influence of AI technology on industry development and organizational structure, as well as innovation and entrepreneurship. However, there is a deficiency in the existing research on **how enterprises use AI technology to develop their ability to cope with environmental impact in a complex and dynamic environment.** What is the effectiveness mechanism of AI technology adoption? Currently, the research on slack resources is advancing into a more in-depth stage, focusing on the categorization of these resources. Singh (1986) also confirmed that slack resources with different nature have different impacts on enterprises. Although scholars have reached a consensus on the basic direction of theory development in this field, the classification of slack resources in the existing research remains unclear. Furthermore, the measurement of each dimension after classification encounters greater challenges. Research in this area is still in the nascent stages. The research questions in this study are formulated within this sequence of thought, aiming to further explore the distinct roles that high-liquidity slack and low-liquidity slack play in the process of developing organizational resilience.

3. Research on the Impact of AI Technology Adoption on Organizational Resilience of Service Enterprises

3.1 Foreword

Sub-study 1 will explore how AI technology adoption affects organizational resilience by increasing high-liquidity and low-liquidity slack resources from the perspective of organizational learning. In addition, this sub-study also examines the moderating effects of two situational factors: diversification strategy and enterprise scale.

This sub-study adopts CSMAR to verify the proposed theoretical model. This sub-study will make contributions to the existing literature from the following aspects: Firstly, by analyzing the influence of AI technology on organizational resilience, the sub-study contributes to the research on the antecedents of organizational resilience in the digital era. Secondly, from the perspective of slack resources, this sub-study opens up the "black box" concerning how AI technology adoption influences organizational resilience and expands research on the specific effect of AI technology adoption on organizational resilience. Thirdly, by analyzing the key contextual variables related to the efficacy of AI technology, the sub-study is conducive to further understanding the boundary conditions that determine the effectiveness of AI technology.

3.2 Research Model and Hypotheses

In the digital era, digital technology exerts a huge effect on business activities, in terms of organizations' resource acquisition, capability development, and structure (Hanelt et al., 2021; Li et al., 2018; Nambisan et al., 2019; Verhoef et al., 2021; Warner & Wager, 2019). The emergence and development of AI technology have had a huge effect on individuals, enterprises, and industries. The existing literature defines AI as a system's ability to learn from data and achieve specific goals and tasks (Haenletin & Kaplan, 2019). Studies on organizational resilience often emphasize the antecedents that contribute to its development. They seek to understand why an enterprise is less vulnerable to shocks than other enterprises and uncover effective strategies for managing crises to achieve enhanced resilience performance. Facing the rapid development and application of AI technology, we explore how AI technology helps enterprises maintain organizational stability and resilience through sustained flexibility.

3.2.1 Main effect hypothesis

AI technology adoption has had a great positive effect on service enterprises. Some studies proposed that digital technology might cause ethical problems (Xie et al., 2019), or impose challenges for organizational management, hindering organizational agility (Liu et al., 2018). However, most scholars recognize the role of AI technology in improving organizations' ability to obtain information and coordinate internal and external resources. They believe that AI technology brings more advantages than disadvantages to enterprises (S. Li et al., 2023; Wu et al. 2022; Y. Zhang & Wang Yonggui, 2022).

Firstly, AI technology adoption improves organizations' ability to acquire and process information. When faced with external shocks, organizations often encounter information that is overwhelming in quantity, challenging to interpret in content, and difficult to assimilate quickly due to time constraints, all stemming from the complexities of the external environment. AI technology adoption effectively assists enterprises in swiftly analyzing vast amounts of information that would otherwise be challenging to process and interpret by optimizing algorithms. This allows enterprises to efficiently acquire information from more channels and sources when compared to their counterparts within the interdependent relationship of the environment. Such information empowers them to make decisions in a volatile setting, consequently bolstering their organizational resilience (DesJardine et al., 2019). For example, Yunji Technology, Huiyi Technology, Joint Wisdom, BTG Homeinns, and Meadin.com have released their respective “Hotel AI Models.” AI technology assists service enterprises and organizations in collecting and processing massive data. Also, it enables them to learn from and analyze such information to enhance decision-making processes amidst external impacts, thus maintaining organizational resilience at the stability level.

Secondly, AI technology adoption improves an organization’s ability for internal and external coordination. Coordination ability is essential for an organization to resist external interference. Only through internal harmony and external coordination can an organization survive in complex environments. AI technology enables “modular” communication between various departments within an organization and ensures efficient and high-quality internal sharing of information, enhancing the organization’s ability for internal coordination. Moreover, AI technology empowers organizations to maintain better coordination with the external environment, ensuring organizational resilience during periods of impact. For example, Country Garden has leveraged AI technology to transform the old communication app, *yuanbao*, integrating its major business of real estate, robots, and agriculture and enhancing its internal coordinating ability. Additionally, it has shifted from passively accepting demand to actively exploring demand, thus achieving a higher level of synergy with the external environment.

H1: AI technology adoption positively affects organizational resilience.

3.2.2 Mediating effect hypothesis

In addition to having a direct impact on organizational resilience, AI technology adoption may also indirectly promote the development of organizational resilience through slack resources. Slack resources are excess resources accessible to an organization during a set planning cycle (Bromiley, 1991). Slack resources are the “sandbag” for enterprises to buffer external shocks and an important factor in forming organizational resilience (Linnenluecke, 2017; Williams et al., 2017). By leveraging AI technology, enterprises can effectively increase both high-liquidity and low-liquidity slack resources, thus boosting their organizational resilience.

The problem of slack resources is more prominent in service enterprises than in other industries. Service enterprises often encounter more slack resources due to the seasonal nature of their operations and substantial fixed-asset investments. Nevertheless, these resources may not effectively assist them in weathering external shocks (Liu Bing, 2015). From the perspective of management flexibility, high-liquidity slack resources, such as cash and cash equivalents, possess higher management flexibility and can be used in a wider range of scenarios. Low-liquidity slack resources, however, have less management flexibility and are only suitable for specific situations, like relatively high employee remuneration, administrative expenses, sales expenses, equipment maintenance and repair costs, and idle equipment (Sharfman et al., 1988). High-liquidity slack resources can be applied to more scenarios. This adaptability enables enterprises to timely adjust strategies and innovate behaviors in response to shocks, effectively cushioning the environmental impact. In the early stage of enterprise development, enterprises might struggle to attain a high return on investment for low-liquidity slack resources, resulting in a lower performance level. However, by utilizing these resources to form economies of scale and create brand effects, service enterprises can maintain competitive advantages in the face of shocks. **Therefore, both types of slack resources in service enterprises may bolster organizational resilience.**

AI technology adoption effectively increases the high-liquidity slack of service enterprises. Big data and AI equip cultural service enterprises with enhanced efficiency, productivity, and profitability while offering customers personalized, convenient, and enriched experiences (Samara et al., 2020). AI technology adoption can directly bring economic effects to service enterprises, enhancing their profitability (Wei Xin et al., 2021), and generating a substantial increase in cash flow. Furthermore, AI technology adoption assists service enterprises in acquiring and processing information more effectively, aiding managers in allocating resources for decision-making more efficiently. This overall enhancement in decision-making efficiency and labor productivity within the service industry leads to increased returns and a rise in high-liquidity slack. High-liquidity slack is retained within enterprises, which has a wide application range and provides managers with an expanded selection of resource options (Sharfman et al., 1988). High-liquidity slack can be conveniently used in various scenarios, allowing companies to trade for other necessary resources when needed. This enhances the flexibility of enterprise resources and enables enterprises to more adeptly cope with internal contradictions or the stress associated with the fluctuating external environment (Combs et al., 2011; Greve, 2007; Huang & Chen, 2010; Moses, 1992). This can also buffer the damage of risks to a certain extent and ensure the normal operation of enterprises, thus enhancing their ability to withstand risks (ArgilSs-Bosch, Garcia-Blandon & Martinez-Blasco, 2016; George, 2005). Additionally, possessing more high-liquidity slack resources enables enterprises to enhance communication with consumers, foster internal learning, and increase exchanges with external organizations, thereby bolstering their ability to recover from risks (Chen & Huang, 2010; Huang & Li, 2012). In addition, possessing more high-liquidity slack resources allows enterprises to try various new projects freely, helping them seize new opportunities and resume development (Miller & Leiblein, 1996; Tan & Peng, 2003). Therefore, enterprises that possess more high-liquidity slack resources are better equipped to withstand and recover from risks.

AI technology adoption effectively increases the low-liquidity slack of service enterprises. AI technology adoption enhances service enterprises' ability for internal and external coordination. For management and marketing processes, AI technology is conducive to faster and better employee and customer management. Moreover, innovative algorithms are revolutionizing marketing models. However, AI technology adoption puts forward higher requirements for the sales and management of service enterprises and increases the complexity of management (Levesque et al., 2022). AI technology adoption has an impact on the employment, service processes, costs, and management methods of service enterprises (Baggio & Cooper, 2013). From the perspective of tourists and customers, patterns such as intelligent customer service, targeted information delivery, and robotic sensing service substantially influence consumer needs, preferences, decision-making, and experience (Ivanov & Webster, 2017). Wei Xiang (2022) pointed out that the digital economy stimulates innovation in tourism-related big data, smart tourism, and tourism blockchain through interactive virtual-real iterations, optimal allocation of resources, and transcending value boundaries. AI technology requires service enterprises to optimize the allocation of management personnel. Service enterprises with a higher level of AI technology adoption put more attention and resources into AI-assisted external marketing and internal management information systems. Therefore, the proportion of marketing and management costs for service enterprises is likely to see a substantial increase, increasing low-liquidity slack.

Based on the above reasoning, we propose the following hypotheses:

H2a: AI technology adoption positively affects high-liquidity slack.

H2b: AI technology adoption positively affects organizational resilience through high-liquidity slack.

H3a: AI technology adoption positively affects low-liquidity slack.

H3b: AI technology adoption positively affects organizational resilience through low-liquidity slack.

3.2.3 Moderating effect hypothesis

Due to the difference in enterprise strategies and scale, AI technology adoption has different effects on slack resources. How service enterprises use AI technology to increase both types of slack resources and thus cultivate organizational resilience depends on their business diversification and enterprise scale.

We first consider the strategic design of enterprises. Their business diversification is closely related to AI technology adoption. The diversification strategy means that enterprises operate a variety of business, with diversified revenue sources and multiple information sources. In contrast, enterprises that adopt the specialized strategy operate a smaller portfolio of business and have more concentrated revenue sources. Technology usage disadvantages refer to the disadvantages that start-ups encounter when entering an industry in which mainstream technology is immature (Chalmers, 2021). Whether AI technology adoption can increase enterprises' slack resources and competitive advantages depends on the acquisition of high-quality data, including initial data and dynamic data (Li Xiaohua & J. Li, 2022). The acquisition of initial data cannot ensure that enterprises attain sustainable competitive advantages. Instead, dynamic data is the foundation for algorithm iteration and the formation of enterprises' dynamic abilities. To ensure AI technology adoption serves the cultivation of a company's sustainable competitive abilities, it is essential to gather a plethora of data assets based on various application scenarios. Moreover, establishing internal cloud systems to support data storage and generation is crucial in this endeavor. For enterprises that are relatively specialized, present for a short period, or small in scale, ensuring diversity in data scenarios can be challenging.

Some scholars believe that AI technology adoption needs to rely on multi-scenario data collection (Wu et al., 2022) because diverse application scenarios enrich the foundation of machine learning. However, applying AI technology to diversified business platforms may incur significant costs (Liu et al., 2018). This is not conducive to improving the profitability of enterprises through AI technology services and may also result in information redundancy. For enterprises that adopt more diversified strategies, AI technology adoption may incur higher costs. Consequently, the role of AI technology in increasing high-liquidity slack may be weakened. In other words, for enterprises engaged in more diversified business, AI technology adoption may cause operational burdens to them, which may hinder the growth of their current assets ratio. Therefore, the diversification strategy weakens the effect of AI technology adoption on high-liquidity slack.

On the other hand, the diversification strategy combined with the information brought about by AI technology may result in the formation of more low-liquidity slack. Low-liquidity slack resources include relatively high employee remuneration, administrative expenses, sales expenses, equipment maintenance and repair costs, and idle equipment (Sharfman et al., 1988). For enterprises with a larger business scope, the role of AI technology adoption in promoting low-liquidity slack resources becomes stronger. Specifically, AI technology adoption increases the management costs and decision-making difficulty of enterprises. The diversification strategy of enterprises causes more scenario information and information processing problems. This puts forward higher requirements for the decision-making abilities of managers as well as their marketing ability and marketing scope. Therefore, the diversification strategy enhances the positive relationship between AI technology adoption and low-liquidity slack (mainly manifested in the proportion of marketing expenses and administrative expenses).

Based on the above analysis, we propose the following hypotheses:

H4a: The diversification strategy negatively adjusts the relationship between AI technology adoption and high-liquidity slack.

H4b: The diversification strategy positively adjusts the relationship between AI technology adoption and low-liquidity slack.

AI technology adoption enhances the effectiveness of high- and low-liquidity slack resources and is also influenced by enterprise scale. Differences in enterprise scale influence enterprise behaviors (Hambrick & Mason, 1984). AI technology adoption increases the management complexity and the difficulty of decision-making. Currently, AI based on deep learning algorithms is like a black box because the intermediate processes through which managers get output results from specific inputs are uncontrollable. Existing AI systems remain weak (X. Sun et al. 2020), i.e., AI abilities are limited to specific domains, exhibiting a significant gap from achieving artificial general intelligence (AGI). Therefore, it is difficult to solve intricate problems in a complex society merely by relying on the progress of AI technology. The effect of human-machine combined decision-making systems is influenced by enterprise scale. Some studies based on agency theory believe that managers, driven by self-interest, may create low-liquidity slack resources, increasing the costs of enterprises (Mishina et al., 2004; Mod & Mishra, 2011). Some scholars point out that enterprises with many low-liquidity slack resources can reduce expenditures in the face of risks by cutting administrative expenses, reducing employee remuneration, and selling idle equipment, which is beneficial to maintaining the normal operation of enterprises (Bourgeois & Singh, 1983; Singh, 1986). However, these measures often damage the vested benefits of employees, cause insecurity at work, and provoke certain resistance. Moreover, there are challenges in re-exploiting these resources and it takes a long time for these resources to play their roles, so these resources may not play their due roles when enterprises confront risks (Chen & Huang, 2010; Cheng & Kesner, 1997; Miller & Leiblein, 1996). In addition, abundant low-liquidity slack resources may also lead to the self-satisfaction of managers (Darmeels, 2008; Kraatz & Zajac, 2001), resulting in a decreased risk perception within enterprises, reducing their subjective initiative to respond to environmental changes (Debruyne et al., 2010; Paeleman & Vanacker, 2015). As enterprises grow in size, integrating AI technology into their internal operations and external interaction scenarios can lead to a significant amount of information redundancy, increasing operational costs and raising operational requirements. This hampers the improvement of profit efficiency through AI technology services for enterprises. Consequently, the role of AI technology adoption in increasing high-liquidity slack may be weakened in large-scale enterprises. In addition, the application of AI systems in large-scale enterprises may involve more scenarios and entail a greater volume of information processing. This puts forward higher requirements for managers' decision-making and marketing abilities, leading to a rise in the proportion of management and marketing costs to total costs. The enterprise scale thus enhances the positive effect of AI systems on low-liquidity slack.

Based on the above analysis, we propose the following hypotheses:

H5a: The enterprise scale negatively adjusts the relationship between AI technology adoption and high-liquidity slack.

H5b: The enterprise scale positively adjusts the relationship between AI technology adoption and low-liquidity slack.

3.2.4 Empirical research model

To sum up, sub-study 1 constructs the theoretical model of "AI technology adoption–liquidity of slack resources–organizational resilience" and analyzes the key scenarios at the business level (diversification strategy) and enterprise level (enterprise scale). AI technology adoption effectively improves organizational resilience, and high- and low-liquidity slack resources play a mediating role in AI technology adoption and organizational resilience. Additionally, the diversification strategy negatively adjusts the positive relationship between AI technology adoption and high-liquidity slack, and positively adjusts the positive relationship between AI technology adoption and low-liquidity slack. The enterprise scale negatively adjusts the positive relationship between AI technology adoption and high-liquidity slack, and positively adjusts the positive relationship between AI technology adoption and low-liquidity slack.

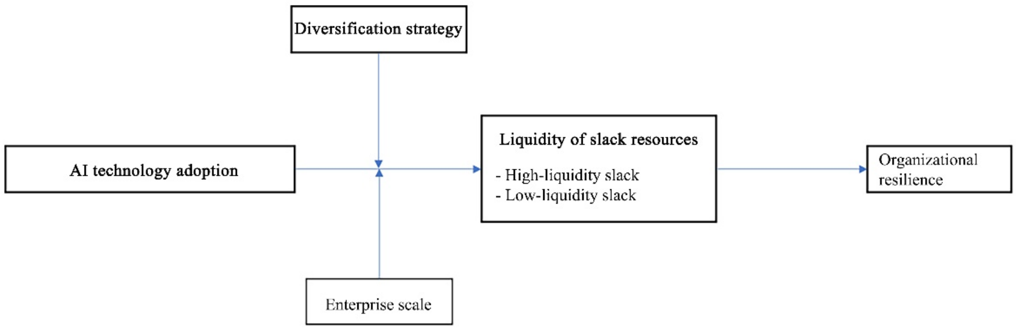

Figure 3.1 Theoretical Model of Sub-study 1

3.3 Research Method

(1) Sample selection

Sub-study 1 selects service enterprises listed in the A-share market in Shanghai and Shenzhen from 2010 to 2020 as the research samples. After 2010, the United States rose strongly and China-US trade frictions continued. Additionally, the European debt crisis in 2012, the Russia-Ukraine confrontation in 2014, the Federal Reserve's interest rate hike in 2015, the European refugee crisis in 2016, and the COVID-19 pandemic in 2020 all had great impacts on the normal operations of enterprises. Therefore, this study identifies 2010 as the starting point for the research samples (Hu et al., 2021).

The sample data are mainly from CSMAR and enterprise annual reports. The sample selection follows the following principles: (1) Matching the establishment year data of A-share listed companies, selecting enterprises within a ten-year interval as research samples; (2) Excluding financial sector enterprises due to the distinctive nature of financial data structures in this study; (3) Removing sample companies with missing data. This study ultimately identifies 225 listed service enterprises, encompassing approximately 1,937 samples in a 10-year range.

(2) Variable measurement

Organizational resilience. The research on organizational resilience reveals significant differences in the measurement of organizational resilience. Some researchers measured organizational resilience by assessing the magnitude of stock price fluctuations and the time taken to recover to the original level. Due to the irrationality and inefficiency existing in China’s securities market, this study does not use stock price data for the measurement of organizational resilience. Hillmann et al. believe that stability is the most important feature of organizational resilience (Hillmann & Guenther, 2021). This perspective highlights that organizational flexibility and stability are reflected in the stability of organizational performance. Therefore, we use the three-year volatility of profits (i.e., the standard deviation of the three-year net profits) as a measure of organizational resilience.

AI technology adoption. Existing studies have explored different ways to measure the concept of AI technology adoption (Cao et al., 2021; Kros et al., 2011; Rahman et al., 2021). Based on the above studies, we use the AI technology-related keyword frequency in enterprise annual reports to measure AI technology adoption. The keywords include machine learning, AI, facial recognition, business intelligence, identity authentication, deep learning, biological intelligent identification, image understanding, semantic search, automatic speech recognition, intelligent robots, intelligent data analysis, autonomous driving, natural language processing, etc. The robustness testing section will also be conducted using alternative measurements, such as word frequency as a percentage of the total words in the annual reports.

Liquidity of slack resources. Based on the measurement of the liquidity of slack resources in existing literature, this study uses financial indicators to measure the liquidity of slack resources. The high-liquidity slack is measured using the current ratio, i.e. the ratio of total current assets to total current liabilities (Li Xiaoxiang & C. Liu, 2010; Liu Bing, 2015). Given the particularity of service enterprises, this study uses the ratio of the sum of sales expenses and administrative expenses to sales revenue to measure low-liquidity slack (Lyer & Miller, 2008).

Diversification strategy. The diversification strategy is measured using the Herfindahl-Hirschman Index of enterprises' revenue across various industries. Pi represents the proportion of the i^{th} industry in an enterprise's total revenue. The larger this index, the lower the level of diversification (the maximum value is 1).

Diversification strategy=ΣPi^2

Enterprise scale. The enterprise scale is measured using the natural logarithm of annual total assets.

Control variables. This study controls the variables that may influence the dependent variable at multiple levels. Firstly, it takes into account the basic features of enterprises, such as enterprise age (G. Sun et al., 2021), as well as organizational structure and management variables (J. Zhang et al., 2022; Linnenluecke, 2017; Vegt et al., 2015), such as equity nature, the number of directors, the proportion of independent directors, and the shareholding ratio of the top 10 shareholders. Furthermore, the study also includes control variables at the financial level of enterprises, such as net ROA (Li Hongquan & Huang, 2011) and the growth rate of operating revenue (Liu Bin & Tan, 2022).

(3) Data analysis

This study plans to employ the fixed effects model for empirical analysis. Firstly, to determine whether to use a panel data model or a mixed OLS model, this study uses the Breusch-Pagan Lagrange Multiplier Test to determine if the data rejects the null hypothesis of homoscedasticity satisfied by random errors. Secondly, to determine whether to use a fixed effects model or a random effects model, this study uses the Durbin–Wu–Hausman test to assess if individual effects are uncorrelated with explanatory variables.

3.4 Data Analysis

(1) Descriptive statistics

Table 3.1 Descriptive Statistics Table

Variable	(1) Sample size	(2) Mean value	(3) Standard deviation	(4) Minimum value	(5) Maximum value
Organizational resilience	1,937	.956	.078	.133	1.000
AI technology adoption	1,937	9.329	19.16	1	258
High-liquidity slack	1,937	2.719	3.095	.028	43.45
Low-liquidity slack	1,937	.210	.237	.003	6.745
Diversification strategy	1,937	.790	.249	.127	1
Enterprise scale	1,937	22.32	1.355	18.59	28.26
Enterprise age	1,937	18.23	6.31	4	119
Net ROA	1,937	.0455	.220	-3.514	.723
Growth rate of operating revenue	1,937	.180	.629	-.891	16.12
Proportion of independent directors	1,937	.380	.0535	.250	.625
Shareholding ratio of the top 10 shareholders	1,937	.575	.157	.152	.949
Equity nature	1,937	.275	.446	0	1
Number of directors	1,937	2.114	.200	1.386	2.773

Firstly, this study conducts descriptive statistics on the main variables (total sample size: 1,937). The dependent variable organizational resilience has a mean value of .956, with a maximum value of 1 and a minimum value of .133; the independent variable AI technology adoption has a mean value of 9.329, with a maximum value of 258 and a minimum value of 1; the mediating variables include high-liquidity slack, exhibiting a mean value of 2.719, with a maximum value of 43.45 and a minimum value of .028, and low-liquidity slack, exhibiting a mean value of .21, with a maximum value of 6.745 and a minimum value of .003; the moderating variables include the diversification strategy, presenting a mean value of .790, with a maximum value of 1 and a minimum value of .127, and the enterprise scale, showing a mean value of 22.32, with a maximum value of 28.26 and a minimum value of 18.59. The descriptive statistics of other control variables are shown in Table 3.1.

(2) Correlation analysis

This study conducts a correlation analysis on the main variables to generate a correlation coefficient table for each variable (see Table 3.2). The results of the correlation analysis indicate a high correlation among the main variables. Among them, AI technology adoption is significantly positively correlated with organizational resilience as well as with high- and low-liquidity slack resources. This relationship can be further explored through regression analysis.

Table 3.2 Correlation Coefficient Table

	Organizational resilience	AI technology adoption	High-liquidity slack	Low-liquidity slack	Diversification strategy	Enterprise scale	Enterprise age	Net ROA	Growth of operating revenue	Proportion of independent directors	Shareholding ratio of the top 10 shareholders	Equity nature	Size of the Board of Directors
Organizational resilience	1												
AI technology adoption	.005**	1											
High-liquidity slack	.002	.09***	1										
Low-liquidity slack	-.004	.045***	.116***	1									
Diversification strategy	-.001	.072***	-.074***	-.01	1								
Enterprise scale	.026*	-.049***	-.312***	-.247**	.049***	1							
Enterprise age	-.003	-.059***	-.172***	-.029**	.100***	.202***	1						
Net ROA	.036**	.010	.076***	-.103***	-.025*	.105***	-.058***	1					
Growth of operating revenue	.000	-.0050	-.006	-.012	.032**	.050***	.009	.008	1				
Proportion of independent directors	-.018	-.022	.054***	.043***	.002	-.015	-.005	-.013	-.012	1			
Shareholding ratio of the top 10 shareholders	.012	-.110***	.029**	-.124***	-.059***	.243***	-.184***	.172***	.04***	-.037***	1		
Equity nature	.028**	-.114***	-.129***	-.11***	.126***	.268***	.212***	.014	-.016	-.074***	.084***	1	
Size of the Board of Directors	.024*	.013	-.123***	-.06***	.032**	.260***	.066***	.046***	.037***	-.557***	.102***	.211***	1

*** p<.01, ** p<.05, * p<.1

(3) Benchmark regression analysis

The study conducted hypothesis testing on the main effects through multivariate regression analysis and employed the three-step regression method to test for the mediating effects. Detailed results are presented in Table 3.3. Model 1 tests the effect of AI technology adoption on organizational resilience, revealing a positive coefficient and a significant effect ($p < .05$). This indicates that Hypothesis 1—AI technology adoption positively affects organizational resilience—is verified.

Models 2 and 3 examine the mediating effect of high-liquidity slack. Model 2 shows that AI technology adoption has a significant positive effect on high-liquidity slack ($p < .01$), with a coefficient of .004. Model 3 shows that AI technology adoption has a positive effect on organizational resilience through high-liquidity slack ($p < .01$), thereby verifying the mediating effect. Hypothesis 2a and Hypothesis 2b are affirmed. Models 4 and 5 examine the mediating effect of low-liquidity slack. The test results of Model 4 show that AI technology adoption has a significant positive effect on low-liquidity slack ($p < .01$), but the test results of Model 5 show that AI technology adoption does not have a significant effect on organizational resilience through low-liquidity slack. Hypothesis 3a is supported, but Hypothesis 3b is not. In other words, AI technology adoption can increase enterprises' high- and low-liquidity slack resources, but the two types of slack resources have distinct impacts on organizational resilience. AI technology adoption can enhance organizational resilience through high-liquidity slack, but the impact path through low-liquidity slack is not supported by data. It is probably because the path or conditions for bolstering organizational resilience through low-liquidity slack in service enterprises should be further clarified.

Table 3.3 Benchmark Regression Model Table

Variable	(1) Organizational resilience	(2) High-liquidity slack	(3) Organizational resilience	(4) Low-liquidity slack	(5) Organizational resilience
AI technology adoption	.000**	.004***	.000***	.002***	.000**
	(2.48)	(4.35)	(2.89)	(2.76)	(2.50)
High-liquidity slack			.002***		
			(3.30)		
Low-liquidity slack					-.004
					(-.52)
Enterprise scale	.005***	-.303***	.003**	-.181***	.004***
	(3.64)	(-16.20)	(2.35)	(-8.08)	(3.59)
Enterprise age	.008	-.273***	.006	-.104*	.008
	(1.53)	(-3.12)	(1.24)	(-1.73)	(1.52)
Net ROA	.223***	.649***	.225***	-.335***	.222***
	(7.44)	(7.27)	(7.46)	(-3.32)	(7.42)
Growth rate of operating revenue	-.004	.002	-.004	-.193**	-.004
	(-1.31)	(.02)	(-1.32)	(-2.21)	(-1.33)
Proportion of independent directors	-.008	.452	-.005	2.120*	-.006
	(-.21)	(.94)	(-.15)	(1.83)	(-.18)
Shareholding ratio of the top 10 shareholders	-.014	.525***	-.010	-.599***	-.014
	(-1.13)	(2.82)	(-.84)	(-4.22)	(-1.18)
Equity nature	.025***	.009	.025***	-.091	.025***
	(9.11)	(.15)	(9.12)	(-1.49)	(9.02)
Number of directors	.020**	-.275***	.019**	.609	.021**
	(2.14)	(-2.65)	(1.99)	(1.61)	(2.20)
Constant term	-.210***	8.502***	-.170***	1.422	-.207***
	(-6.22)	(16.77)	(-4.50)	(1.57)	(-6.09)
Sample size	1,937	1,937	1,937	1,937	1,937

Robust z-statistics in parentheses

*** p<.01, ** p<.05, * p<.1

(4) Regression analysis of the moderating effect

Table 3.4 Moderating Effect Table

Variable	(1) High-liquidity slack	(2) High-liquidity slack	(3) High-liquidity slack	(4) Low-liquidity slack	(5) Low-liquidity slack	(6) Low-liquidity slack
AI technology adoption	.005***	.005***	.005***	.002***	.002**	.002**
	(5.00)	(4.48)	(5.57)	(2.83)	(2.37)	(2.24)
Diversification strategy	-.032	-.060***	-.030	-.048*	-.037*	-.048*
	(-1.36)	(-2.72)	(-1.29)	(-1.93)	(-1.72)	(-1.94)
Enterprise scale	-.302***	-.287***	-.286***	-.178***	-.181***	-.182***
	(-16.21)	(-15.78)	(-15.77)	(-8.26)	(-8.06)	(-8.01)
AI technology adoption*diversification strategy	-.002***		-.003***	.001		.001
	(-2.59)		(-3.44)	(1.42)		(1.61)
AI technology adoption*enterprise scale		-.002**	-.003***		.001	.001
		(-2.34)	(-3.38)		(.91)	(1.33)
Enterprise age	-.256***	-.268***	-.265***	-.093	-.092	-.091
	(-2.96)	(-3.04)	(-3.06)	(-1.54)	(-1.52)	(-1.48)
Net ROA	.645***	.634***	.635***	-.335***	-.333***	-.333***
	(7.25)	(7.04)	(7.13)	(-3.34)	(-3.33)	(-3.34)
Growth rate of operating revenue	.001	.003	.003	-.193**	-.195**	-.193**
	(.01)	(.05)	(.05)	(-2.21)	(-2.22)	(-2.23)
Proportion of independent directors	.442	.479	.489	2.113*	2.105*	2.101*
	(.92)	(1.00)	(1.03)	(1.83)	(1.83)	(1.83)
Shareholding ratio of the top 10 shareholders	.519***	.473**	.465**	-.609***	-.599***	-.598***
	(2.81)	(2.52)	(2.51)	(-4.25)	(-4.20)	(-4.19)
Equity nature	.013	.024	.026	-.085	-.090	-.088
	(.21)	(.40)	(.43)	(-1.41)	(-1.47)	(-1.44)
Number of directors	-.281***	-.271***	-.273***	.604	.601	.600
	(-2.71)	(-2.60)	(-2.61)	(1.61)	(1.61)	(1.61)
Constant term	8.505***	8.260***	8.194***	1.425	1.466*	1.502*
	(16.79)	(16.39)	(16.17)	(1.58)	(1.65)	(1.71)
Sample size	1,937	1,937	1,937	1,937	1,937	1,937

Robust z-statistics in parentheses

*** p<.01, ** p<.05, * p<.1

Table 3.4 shows the results of the regression analysis of the moderating effect model. Models 1 and 2 test the results of the moderating effect on the relationship between AI technology adoption and high-liquidity slack. Model 1 reveals that the interaction term between the diversification strategy and AI technology adoption negatively influences high-liquidity slack ($p<.01$, $\beta=-.002$). Model 2 shows that the interaction term between enterprise scale and AI technology adoption negatively influences high-liquidity slack ($p<.05$, $\beta=-.002$). This also affirms Hypothesis 4a: The diversification strategy negatively adjusts the relationship between AI technology adoption and high-liquidity slack. Also, it supports Hypothesis 5a: The enterprise scale negatively adjusts the relationship between AI technology adoption and high-liquidity slack. Model 3 indicates that the interaction term between the diversification strategy and AI technology adoption has no significant effect on low-liquidity slack. Similarly, Model 4 reveals that the interaction term between enterprise scale and AI technology adoption has no significant effect on low-liquidity slack. Consequently, Hypotheses 4b and 5b are not supported by data.

3.5 Research Conclusions

Sub-study 1 addressed the key research question of "How does AI technology adoption affect the organizational resilience of service enterprises" by analyzing second-hand data. It constructed a model concerning the effect of AI technology adoption on the organizational resilience of service enterprises through theoretical deduction and proposed eight hypotheses. Among them, the main effect hypothesis—AI technology adoption positively affects organizational resilience—is supported by data; the mediating effect of high-liquidity slack is significant; and the moderating effect of the diversification strategy and enterprise scale on AI technology adoption and high-liquidity slack is also supported. However, empirical research reveals that the effect of enterprise scale and the diversification strategy is not significant in the relationship between AI technology adoption and low-liquidity slack. This could be because, in the operational context of service enterprises, the impact of increased AI technology adoption on low-liquidity slack is reflected in the rise of the proportion of management and advertising expenses. This is due to the heightened complexity of management brought about by AI technology, which raises the bar for managerial personnel. The reason why enterprise scale does not have a significant moderating effect might be that this study selected listed enterprises as the research samples. These samples do not cover most unlisted service enterprises, so the scale difference among listed enterprises cannot be significantly reflected in management costs and management modes. The lack of a significant moderating effect of the diversification strategy could be due to the different choices of diversified strategies between service and manufacturing enterprises. Service enterprises might opt for business operations closer to their core business, even though this significantly increases the scenarios and costs associated with AI technology adoption. Consequently, this negatively moderates the positive impact of AI technology adoption on high-liquidity slack. However, there is no apparent change in the requirements for management models. For specific conclusions, please refer to Table 3.5:

Table 3.5 Hypothesis Testing Conclusions

Hypothesis	Regression analysis results
H1 AI technology adoption positively affects organizational resilience	Positively significant
H2a AI technology adoption positively affects high-liquidity slack	Positively significant
H2b The mediating effect of high-liquidity slack	Positively significant
H3a AI technology adoption positively affects low-liquidity slack	Positively significant
H3b The mediating effect of low-liquidity slack	Insignificant
H4a The diversification strategy negatively adjusts H2a	**Negatively** significant
H4b The diversification strategy positively adjusts H3a	Insignificant
H5a The enterprise scale negatively adjusts H2a	**Negatively** significant
H5b The enterprise scale positively adjusts H3a	Insignificant

In practice, AI technology adoption in service enterprises may affect organizational resilience directly or indirectly. By analyzing data from listed enterprises, this study reveals that AI technology adoption has a significant positive effect on organizational resilience, indicating that AI technology adoption can help service enterprises better cope with external environmental impacts. In addition, AI technology adoption can indirectly bolster organizational resilience by increasing the high-liquidity slack of service enterprises, thus enriching the research on the antecedents of organizational resilience. From 2020 to 2022, most service enterprises were adversely impacted by the COVID-19 pandemic, experiencing negative repercussions on their operations and survival. However, a considerable number of service enterprises completed digital transformation by adopting AI technology during the pandemic. These enterprises managed to gain new competitive advantages and quickly recovered from external shocks, thereby maintaining good enterprise performance. The following section will take these typical enterprises as cases to further reveal the influence mechanism of AI technology adoption on organizational resilience.

4. Case Studies of Service Enterprises Fostering Organizational Resilience through AI Technology Adoption in Response to the Impact of COVID-19

4.1 Research Design

Over the past three years, the majority of service enterprises have faced significant operational challenges due to the impact of the pandemic. The ability to uphold organizational resilience has emerged as a critical factor for the survival and healthy growth of service enterprises. The development mechanism of organizational resilience has thus emerged as a significant topic of interest in both academic research and practical applications. Existing literature analyzes the antecedents of organizational resilience from the perspectives of organizational capability, organizational resources, and social networks. With the rapid development of digital technology represented by AI, scholars have discussed at different levels how AI can change the position of enterprises in the global value chains (GVCs) (Graetz & Michaels, 2018; Yang & Fan, 2020) and improve industrial structure transformation (Acemoglu & Restrepo, 2019; L. Li et al., 2021; Wang Yongqin & Dong, 2020), and also focused on the impact of AI technology on organizational structure, innovation, and decision-making (Agrawal et al., 2018). Can AI technology foster the organizational resilience of service enterprises? What is the process and mechanism? At present, systematic analysis and answers are not available in relevant literature.

To answer the core research question: How does AI technology adoption affect the organizational resilience of service enterprises, sub-study 2 intends to explore how service enterprises foster organizational resilience using AI technology in response to the impact of COVID-19 by conducting in-depth investigations on several representative service enterprises (mainly cultural tourism enterprises) hit by the pandemic. To address the questions of why and how AI technology adoption affects organizational resilience formation, sub-study 2 adopts a case study method (Eisenhardt, 1989) to delve deeply into the role of AI technology adoption in fostering organizational resilience.

4.2 Research method

Sub-study 2 focuses on case studies of how service enterprises enhance organizational resilience by leveraging AI technology in response to the impact of COVID-19. The case study method is often employed to discuss issues related to cognition and complex situations in organizational research (Muzychenko & Liesch, 2015; Rialp & Knight, 2005). The question to address in this study is how service enterprises employ AI technology to foster organizational resilience in response to the impact of COVID-19. This study employed a multi-case study method, taking enterprises as individual research subjects. It identifies five enterprises as target enterprises and investigates them through semi-structured interviews, field visits, and second-hand data collection.

Table 4.1 Case Data Collection Process

Step	Task	Detail
Stage 1	**Preliminary case data collection and analysis**	
1	Preliminary screening of research subjects (January–September 2022)	Reviewed enterprise information and news reports, and preliminarily screened target service enterprises and interviewees through field visits and introduction of surrounding entrepreneurs.
2	Determination of research subjects (September–November 2022)	Discussed with the instructors and doctoral students of the research team, continuously followed up on the reports related to target enterprises' fight against COVID-19, identified 5-6 service enterprises as target enterprises, and listed their founders or members of top management teams as interviewees.
3	First round of data collection (December 2022–February 2023)	Carried out semi-structured interviews via forms such as field visits or online meetings to complete the interviews of three enterprises, established archives for each enterprise, and performed initial categorization of the text data.
4	Data coding and analysis (February–March 2023)	Carried out the first round of collected data discussion and inductive analysis to determine the interview objectives and sample size for the next stage.
Stage 2	**Sample supplementation and case writing**	
5	Sample supplementation (April 2023)	Identified two enterprises as supplementary samples according to the preliminary analysis results.
6	Second round of interviews (May–June 2023)	Carried out semi-structured interviews via forms such as field visits or online meetings, and transcribed the interview texts to establish a preliminary framework for the study and determine the saturation of the sample size.
7	Data integration and analysis (July 2023)	Compared, integrated, and summarized the analysis results of all text data collected, and discussed the results with the instructors and doctoral students of the research team.
8	Case writing and revision (August–September 2023)	Wrote the case analysis results and revised texts to construct relevant doctoral dissertation chapters.

Table 4.1 presents the data collection process for case studies. The data collection process for case studies mainly consists of eight steps in two stages. The data collection in stage 1 includes preliminary screening and determination of research subjects, the first round of data collection, and preliminary data coding and analysis; the data collection in stage 2 includes sample supplement, the second round of interviews, data integration and analysis, and case writing and revision.

The data collection and analysis for the entire case study required 1.5 years.

In the selection of case enterprises, the performance of listed service enterprises in the empirical research was fully considered, with my management practice referenced. From 2020 to 2022, under the impact of COVID-19, most service enterprises experienced profit decline and business contraction, and some even faced survival threats. Take the catering industry as an example. In the period spanning January to April 2022, the industry experienced a 5.1% [1] decline in revenues. Alongside this overall downturn, the sector encountered numerous practical challenges, including struggles in cutting rental, raw material, and labor costs, as well as a significant decrease in customers. By December 31, 2022, a total of 519,000 catering enterprises had been canceled or had their licenses revoked[2]. Most enterprises that failed to sustain their operations relied on traditional operating models before the pandemic and had not adopted digital technologies such as AI technology to boost their growth. The target enterprises for this study are those that had already adopted AI technology before the pandemic, sustained relatively strong profitability amidst the crisis, and have the capability to leverage AI for decision optimization, strategic transformation, and others. This study finally identified five sample enterprises for case analysis and completed the field research of these enterprises, alongside semi-structured interviews with CEOs or members of top management teams. On average, 2-3 senior executives from each company were interviewed, with average interview duration of 2 hours per person. The interviews included questions regarding the operational status of the sample companies before the impact of the COVID-19 pandemic in 2020, the types of AI technology employed before the pandemic, the specific business modules where

[1]Source: National Bureau of Statistics

[2]Source: qcc.com

this technology was utilized, and the outcomes achieved. Additionally, the interviewees were asked about the biggest challenges faced by their companies during the COVID-19 pandemic, how they tackled these difficulties and challenges, and the role that digital technologies, especially AI technology, played during the pandemic.

To ensure the validity and reliability of the case studies, this study adopted the following strategies: Firstly, a detailed research proposal was formulated before the study, and professors with rich experience in case studies were invited to repeatedly demonstrate the rationality of the proposal. Secondly, in terms of interview process control, researchers informed the interviewees of the purpose of this study and the main interview questions before the interviews, allowing interviewees to have a general understanding of the interview process and engage naturally and objectively in topic discussions. During the interview process, the purpose of the study and the topics of discussion were communicated clearly as far as possible in ways that were recognized by the interviewees. The abstract academic language was avoided, and the rigid adherence to predetermined interview outlines was eschewed. Attention was paid to interactions with the interviewees and uncovering the interviewees' underlying genuine thoughts. Thirdly, diverse sources of evidence were utilized, and data from different sources formed a crossed triangulation relationship, establishing an enriched chain of evidence. After the case study report was drafted, interviewees were invited via email to review the research findings to verify the validity and realness of the evidence. Fourth, throughout the data analysis process, emphasis was placed on shuttling back and forth between data, relevant theories, and existing literature. In the process of continuously refining the research findings, the alignment between data and theory was gradually achieved, enhancing the level of theoretical abstraction. This was done to ensure that the research conclusions could be generalized to other contexts.

4.3 Preliminary Analysis of Sample Enterprises

Firstly, a brief overview of the sample enterprises' information (including their basic information, the pandemic's impact on them, their organizational resources, etc.), as well as AI technology adoption in them, will be presented.

(1) BTG Homeinns

BTG Homeinns was established after the merger of the former BTG Hotels (Group) Co., Ltd. and Homeinns Hotel Group. Homeinns Hotel Group was founded in 2002 and listed on the NASDAQ in the United States in October 2006. Currently, the merged BTG Homeinns boasts nearly 20 brand series and nearly 40 products centered around accommodations. As of the end of June 2022, BTG Homeinns had operated nearly 6,000 hotels in over 600 cities across China, covering a full range of hotel business such as "high-end," "mid-to-high-end," "business travel type," "leisure and resort," "networking and entertainment," and "alliance" hotels.

In 2020, BTG Homeinns achieved annual operating revenues of about RMB 5.282 billion, with a year-on-year decrease of 36.45%. The net loss attributable to the parent company was RMB 496 million, and the net loss attributable to shareholders of the listed company after the deduction of non-recurring profits and losses was RMB 527 million. According to its financial report, BTG Homeinns started to achieve profits from the third quarter of the year. In the third and fourth quarters of 2020, its net profit attributable to shareholders of the listed company after the deduction of non-recurring profits and losses was RMB 133 million and

RMB 45.2775 million, respectively. Since the second half of 2020, BTG Homeinns has continuously optimized its operations to rescue itself and fully promoted digitization. Through collaborations with Internet enterprises and the application of cutting-edge technology, the company has integrated online and offline development and increased the use of live streaming and other digital marketing methods. Focusing on boosting user traffic and conversion rates, it has continued to employ marketing strategies like "live streaming+" to enhance hotel revenue through multiple dimensions.

In the post-pandemic era, as people's consumption behaviors and patterns changed, there has been a marked decrease in the demand for business trips. Business travelers increasingly opted for the online model for business communication. According to a Morgan Stanley report, by 2022, with 27% of business trips being replaced by online meetings, the hotel industry's revenue from business travelers, accounting for about two-thirds of total income, was expected to decline by up to 18%. The demand for "contactless" services among business travelers has increased, driving the hotel industry to conduct technological upgrades. With the continuous application of technologies, the industry has gradually entered an era characterized by a digital boom. In the current exploration of smart hotels, BTG Homeinns is innovating hotel technology while leveraging technology to manage hotel space and clientele. In its digital exploration, it presents an increasing trend toward creating a holistic scene, making technology services more human-centered. The "Annual Smart Innovative Hotel Group" award was a full testament to BTG Homeinns' unwavering commitment to continuous innovation and exploration in smart services. After the outbreak of COVID-19, BTG Homeinns actively participated in pandemic prevention and control and increased investments in hygiene and AI. Specifically, it implemented upgraded hygiene standards, intensified cleaning measures, provided over 3,000 “reassuring hotels,” and introduced blockchain cleanliness tracking technology. To adapt to consumers’ contactless service and smart technology needs during the pandemic, and to reduce operational costs, BTG Homeinns explored machine intelligence services for multiple accommodation links. These included smart rooms, self-service vending machines, delivery robots, online room selection, and more.

(2) SSAW Hotels & Resorts

Founded in 2007 and headquartered in Hangzhou, Zhejiang Province, SSAW Hotels & Resorts is mainly engaged in the operation and management of mid-to-high-end selective service chain hotels. Since its inception, it has focused on the Yangtze River Delta urban agglomeration as its core development area, gradually and systematically expanding operations to major cities nationwide. It has emerged as a pioneer in the mid-to-high-end selective service hotel sector. SSAW Hotels & Resorts stands out with key competitive advantages including expertise in hotel development and design, its distinctive SSAW-style service system, strong brand reputation, extensive customer network, and a skilled management team. These factors have propelled SSAW Hotels & Resorts to rank among the top 50 hotel groups in scale in China. Furthermore, the brand has consistently been recognized among the “Top 60 Hotel Groups in China” for several years in a row. At present, SSAW Hotels & Resorts operates 47 hotels with 19 additional ones under contract for future openings. These establishments are strategically located in key cities and provinces including Shanghai, Zhejiang, Jiangsu, Hubei, Anhui, Jiangxi, and Hainan within China, as well as in Perth, Australia.

Even amidst the challenging environment of the hotel industry and declining performance of hotel enterprises due to the impact of the COVID-19 pandemic that began in 2020, SSAW Hotels & Resorts remarkably achieved outstanding results, including premium acquisitions, soaring stock prices, and impressive growth in performance. On April 29, 2022, SSAW Hotels & Resorts unveiled an updated version of its 2021 annual report. As per the report, the company showcased growth in both revenue and net profit. By the conclusion of 2021, SSAW Hotels & Resorts had accumulated revenues of around RMB 278 million, marking an 8.39% increase compared to the previous year. The net profit amounted to RMB 36.9176 million, reflecting a year-on-year rise of 5.28%. The net profit, excluding non-recurring profits and losses, reached RMB 31.166 million, representing a year-on-year growth of 2.66%. During the reporting period, its various operational metrics recovered significantly.

It has seamlessly incorporated Internet technology into all aspects of hotel operations and management. The customized hotel management system group currently utilized by SSAW Hotels & Resorts comprises the central reservation system, CRM (customer relationship management), PMS (property management system), and more. In 2007, its founder Wu Qiyuan innovatively introduced the “BAS” selective service model to create the brand of SSAW Hotels & Resorts. “BAS” stands for Bed (accommodation), Art (culture and art), and Service. This model emphasizes the provision of high-quality guest rooms as the foundation of its accommodation services while integrating distinctive cultural and artistic theme elements into guest rooms and public space. Additionally, the model also includes offering exclusively designed discounting derivative services for guests.

Boutique hotel services are characterized by efficient service quality control, attention to service details, thoughtfulness, and personalization. Many hotels in this brand have embraced AI technologies like facial recognition for authentication and self-service check-ins, along with robot housekeeper services. Some hotels have spearheaded the transformation to create smart hotel scenarios. For example, guests can intelligently adjust the lighting, temperature, curtain switches, and multimedia equipment operation in guest rooms according to their preferences. It has cooperated with Alibaba Future Hotel to install smart electronic sensor door locks in some hotels, focusing on enhancing customer interaction methods and personalized experiences.

(3) Atour Hotel

Founded in 2013, Atour Hotelpossesses four accommodation product lines: Atour Hotel, Atour Light, long-term rental apartments, and small luxury boutique hotels. Atour Hotel's main strategy revolves around being a mid-tier "cultural hotel," emphasizing life experience scenes and neighborhood services. They enhance their hotel scenes with cultural elements related to reading and photography. Apart from hotels, Atour Hotel has expanded into various sectors including the e-commerce O2O platform "Atour Life Pavilion" and the Internet finance platform "Duoyouqian."

Atour Hotel has recently been successfully listed. Positioned as a lifestyle brand in the mid-to-high-end hotel category, it demonstrated impressive resilience in operations during three-year COVID-19 outbreaks, achieving consistent revenue growth.

Based on its prospectus, Atour Hotel had doubled its number of open hotels by the end of September 2022, increasing from 420 in 2019 to 880. According to the data from Frost & Sullivan, Atour Hotel has ranked first among mid-to-high-end chain hotels in China for five consecutive years from 2017 to 2021 based on the number of hotel rooms.

As the number of locations rapidly expands, Atour Hotel's revenue growth remains on a steady upward trajectory. According to the prospectus, Atour Hotel achieved revenues of RMB 1.567 billion, RMB 1.567 billion, and RMB 2.148 billion in 2019, 2020, and 2021 respectively, maintaining profitability for three consecutive years. It stands out as the sole large-scale hotel company in China to sustain profitability for three years in a row, with net profits of RMB 61 million, RMB 38 million, and RMB 140 million in 2019, 2020, and 2021, respectively.

During the pandemic, Atour's profitability resilience continued to strengthen. In the first three quarters of 2022, Atour saw continued growth in revenue and net profit. In the first nine months of the year, it achieved revenue of RMB 1.637 billion, up 5.23% from the same period last year. Its net profit reached RMB 179 million, up 58.42% year-on-year. Its net profit in the third quarter of 2022 was RMB 111 million, with a net profit margin of 16.6%, hitting a record high. During this period, Atour Hotel demonstrated a strong ability to withstand and recover from risks.

In addition to hotel accommodation, it has succeeded in nurturing a second revenue growth curve through its steady development. Based on the accurate insight into user needs, Atour Hotel has innovatively launched a scenario-based retail business model within the context of scenario application. As of June 30, 2022, it had launched 1,967 SKUs, 62.8% of which are private-label products. These products were divided into three product lines, namely αTOUR planet, SAVHE, and Z2GO&CO., covering a wide range of products such as sleep-related products, personal care products, and travel necessities.

From 2016 to 2021, the compound annual growth rate (CAGR) of Atour Hotel's retail GMV reached 134.5%, with a year-on-year increase of 112.9% in 2021. In the first three quarters of 2022, its retail and other business contributed RMB 227 million to its revenue, with the proportion of its total revenue increasing to 13.9% in the third quarter of 2022 from 7.1% in 2019. These segments emerged as a new growth driver for the brand.

Atour Hotel has also accumulated a large number of members through the A-Card membership program during its consistent growth, boasting 32 million registered members as of June 30, 2022. It achieved a CAGR of 48.7% from 2016 to 2021. In 2021, A-Card members contributed 39.7% to the revenue from room night reservations and their repurchase rate rose to 52.8%.

With its differentiated business philosophy, Atour Hotel took the lead in recovering from the impact of COVID-19. As a leader of domestic hotels focusing on experience, Atour Hotel stays committed to delivering exceptional performance.

(4) Trip.com Group

Trip.com Group is a comprehensive travel service company based in China. It was founded in 1999 and is headquartered in Shanghai, China. The current chairman of the company is Liang Jianzhang. The co-founders are Liang Jianzhang and Fan Min. The company provides a full range of travel services including wireless applications, hotel reservations, air ticket bookings, tourism and vacations, business travel management, travel information, and more. Trip.com Group's brands include Trip.com, Ctrip, Skyscanner, and Qunar. On April 19, 2021, Trip.com Group was listed with the stock code of HK9961.

In the second quarter of 2023, its net operating revenue reached RMB 11.2 billion, marking a year-on-year increase of 180% and a 29% rise compared to the same period in 2019. Following the outbreak of COVID-19, the tourism industry was struck harder than ever before. However, with government support for resuming work and production, as well as relief policies, Trip.com maintained the foundation of the market and the tourism industry. Throughout its pandemic response, Trip.com Group consistently followed the principle of "customer first, partner second, and company third," placing considerable emphasis on fulfilling its social responsibilities while actively carrying out proactive self-help initiatives. During the three-year pandemic, Trip.com Group canceled customer orders worth over RMB 100 billion. It took the initiative to bear the losses caused by suppliers' failure to return orders to consumers, with a cumulative amount of about RMB 560 million. It took measures such as reducing and waiving or subsidizing marketing expenses, compensating for the losses of merchants caused by order changes and refunds due to the pandemic, and accelerating the capital turnover of merchants. By doing so, the company alleviated and reduced nearly RMB 2 billion in burdens for small and medium-sized merchants. Moreover, Trip.com successively issued a range of measures such as the "Partner Plan," "Travel Revival V Plan," and "Travel Revival 2.0 Plan" to foster the recovery of the industry. During the lockdown in Shanghai and other areas in 2022, Trip.com Group actively assisted medical teams, supply guarantee enterprises, and material distribution personnel in solving accommodation difficulties and even the lack of available rooms. It coordinated and ensured over 140,000 room nights for them. Within the three years, the company leveraged its advantages in products, technologies, services, and supply chains and collaborated with upstream and downstream enterprises to maintain the foundation of the market and the industry.

In March 2021, Trip.com Group launched its “rural tourism revitalization” strategy, aiming to build 10 benchmark public welfare farms, empower 100 tourist villages on a large scale, and cultivate 10,000 people for rural tourism revitalization in the next five years. It prioritized the creation of 10 public welfare high-end rural accommodation benchmarking products branded as Ctrip Holiday Farm, to enhance the accommodation experience in rural destinations. After more than one year of development, the company’s “rural tourism revitalization” strategy achieved fruitful results. Leveraging the Ctrip Holiday Farm as a platform, Trip.com Group provided multi-dimensional assistance in empowering rural revitalization with the cultural industry, thereby fulfilling its social responsibility, invigorating the destination tourism economy, and bridging the gap in social resources.

As of 2022, Trip.com Group had established 21 Ctrip Holiday Farms, including three self-operated public welfare farms and 18 joint farms. These farms were distributed in 11 provinces and autonomous regions including Anhui, Henan, Hunan, Xinjiang, Jiangxi, Guangxi, Shaanxi, Inner Mongolia Autonomous Region, and Guizhou. In accordance with Trip.com Group’s “rural tourism revitalization” strategy, the extensive launch of Ctrip Holiday Farms will bolster policy implementation. Additionally, supported by policies, Ctrip Holiday Farms are ready to expedite the discovery of innovative models that blend culture and tourism, with the goal of advancing rural tourism towards high-quality development.

According to data, the operational farms have actively employed local villagers, providing young people with opportunities to return to the countryside.

Local employees account for over 80% of the employed personnel. The average salary of farm staff has increased by more than 60% compared to the local average salary level. The farms have attracted nearly half of non-local tourists to visit and spend locally, also boosting consumption in terms of local scenic area tickets and recreational products. Almost half of the users booking the farms will book train or plane tickets at the same time, and close to 40% of users will also book tickets for nearby scenic areas when booking the farms.

(5) Xibei

Founded on October 10, 2017, and situated in Hohhot, Inner Mongolia Autonomous Region, Inner Mongolia Xibei Catering Group Co., Ltd (hereinafter referred to as “Xibei”), is an enterprise mainly engaged in the catering industry. Under the leadership of founder Jia Guolong, who holds the dual roles of Chairman and General Manager, Xibei mainly provides Chinese casual dining options, with a focus on Northwestern Chinese cuisine. Xibei’s menu features signature dishes such as fish-shaped oat noodles in mushroom soup, Xibei gluten, yellow rice cold cake, and assorted fruit and vegetable platters. According to official statistics, as of March 2023, Xibei had operated 349 stores in 58 cities across 24 provinces in China. On August 8, 2020, Xibei ranked 239th on the top 500 brands list at China Brand Festival 2020 with a brand value of RMB 6.21 billion.

Under the impact of the pandemic, Xibei implemented strategic adjustments to resume operations promptly, yielding the following fruitful results. Firstly, by launching “professional children’s meals,” Xibei achieved an impressive 415% increase in revenue. In June 2022, Xibei officially launched professional children’s meals to reinforce its position as a family-friendly dining destination. Despite the pandemic, Xibei's children's meal segment experienced substantial growth. In 2019-2022, Xibei's revenue from children's meals surged by 415%. Children's meals rose rapidly in popularity in the food delivery market, soaring to the top in sales by August. Secondly, Xibei accelerated the development of its high-quality food delivery offerings, resulting in an 86% boost in this segment. Relying on the pandemic-driven surge in food delivery demand, Xibei achieved sustained and significant growth in its food delivery revenue. From 2019 to 2022, the revenue from food delivery sales sharply increased by 86%. Notably, two of Xibei's branches excelled in food delivery performance: the branch operated by Wang Longlong with a 148% increase, and that managed by Li Fenglan with a 141% rise. Most stores of the two branches were located in the Beijing market. The internal letter revealed Xibei's focus on ensuring quality in its food delivery services. Thirdly, Xibei expedited its shift in the retail business, experiencing a growth of 257% over three years. After the outbreak of COVID-19, the retail transformation in the catering industry emerged as a vital strategic move for industry participants. Leading brands, including Xibei, Haidilao, and Guangzhou Restaurant, ramped up their investment in the retail sector. Xibei, in particular, witnessed leapfrog progress in its retail operations, with retail revenue rising by 257% in 2019-2022. Fourthly, adhering to the principle of providing excellent dining experiences for customers, Xibei saw a 92% revenue increase in five-star-rated stores. Xibei substantially enhanced overall customer satisfaction by prioritizing the distinctive qualities of beef and lamb dishes and optimizing dine-in services, children's meals, food delivery options, and standardized processes. This contributed to a 92% rise in the number of Xibei's five-star-rated stores on Dianping, surging from 49 in 2020 to 94 in 2022. It is reported that Xibei operates about 360 stores, asserting its dominance in the Chinese dining market except for the hot pot segment.

Table 4.2 Basic Information Integration and Preliminary Analysis of Sample Enterprises

Enterprise name	**Industry**	**Market strategy**	**Operation status during the pandemic**	**Digital transformation features**	**AI technology adoption**
BTG Homeinns	Hotel industry	Low cost + franchise-based expansion + multiple business segments	Sustained profitability and business transformation	Digital marketing, e-commerce platforms, online user communities, etc.	Robot applications, smart guest rooms, etc.
SSAW Hotels & Resorts	Hotel industry	Differentiation + expansion in direct sales + single business segment	High profitability and rapid expansion	Smart hotel equipment, outsourcing construction management system, etc.	Intelligent sensing equipment, robot housekeeper, etc.
Atour Hotel	Hotel industry	One focus (user experience) + two strategies (targeted and intelligent operations) + differentiation	Consistent profitability and accelerated expansion over three years	Digital marketing, e-commerce platforms, online user communities, etc.	Robot applications, robot housekeeper service, etc.
Trip.com	Internet/tourism industry	Platform core business + expansion in cultural tourism segment (differentiation)	Rapid post-pandemic recovery, profit growth, and steady segment expansion	Digital management, online user community, self-media marketing, etc.	Robot applications, AI-assisted decision-making, etc.
Xibei Group	Catering industry	Directly operated stores + differentiated services + module expansion of ready-to-cook meals	Surge in growth of children’s meals and ready-to-cook meal segments	Digital marketing, e-commerce platforms, etc.	Robot applications, algorithm analysis, etc.

Through the integration and preliminary analysis of basic information of sample enterprises, it is discovered that the five service enterprises cover the tourism, catering, and hotel industries. Based on my management experience and the accessibility of interview-based data, three hotel enterprises, which are notably distinct in their deployment of market strategies and AI technology adoption, were chosen as sample enterprises. The shared traits among the five enterprises include their completion of certain digital transformation initiatives before the pandemic, the adoption of various AI technologies, and the ability to ensure AI technology adoption in management. These enterprises experienced a brief decline in profits due to the pandemic, but they rebounded more quickly than their peers. They developed new business segments and achieved fresh profit growth, which aligns with the requirements for sample enterprises in this study.

4.4 Research Conclusions

Through a cross-case study, it was observed that the response of the sample enterprises to the impact of COVID-19 unfolded across three stages: (1) In the pre-impact stage during early 2020, China's service enterprises encountered the initial repercussions of COVID-19. The prolonged stay-at-home policy endured for approximately six months, leading to significant setbacks for them. (2) The impact stage from 2020 to 2022 witnessed a more steady spread of the pandemic, expanding affected areas, evolving consumption behaviors, restricted regional mobility, and necessitated strategic adjustments for tourism and catering enterprises. (3) Transitioning to the post-impact stage from late 2022 to 2023, changes in the virus landscape and transmission dynamics allowed for improved regional mobility, creating opportunities for recovery in the service industry. However, this phase also presented new strategic challenges and underscored the need for sustainable development in enterprises. Amid the impact of COVID-19, organizational resilience is exhibited in varying dimensions at distinct stages (Patriarca et al., 2018). The abilities of organizational awareness, utilization, and reconfiguration play a significant role in developing organizational resilience (Teece et al., 1997). The process mechanism through which organizational resilience operates is dynamic (Ma et al., 2018). An organization's cognitive and early warning abilities before an external shock (Kahn et al., 2018), its responsiveness and resource allocation abilities during the shock, and its recovery (Ortiz-de-Mandojana & Bansal, 2016) and learning abilities (Linnenluecke, 2017) post-shock all play significant roles in determining whether it can sustain stable operations amidst the disruption. At each stage, AI technology adoption has played distinct roles in shaping organizational resilience. Specifically, it bolstered enterprises' environmental awareness and information judgment abilities in the pre-impact stage; facilitated algorithm innovation and intelligent decision-making during the impact stage; and assisted enterprises in exploring new paths and capitalizing on fresh entrepreneurial prospects in the post-impact stage.

(1) Pre-impact stage: environmental awareness and information judgment

At the pre-impact stage, organizational resilience is reflected in an organization's environmental awareness, which often relies on its proficiency in gathering information, a well-established management process, and a flexible organizational framework. A key aspect of how digital transformation empowers enterprises is by enhancing their information-gathering capabilities. Furthermore, AI technology adoption helps enterprises acquire vast amounts of information across various scenarios, enhancing their processing abilities of external information.

Advancements in information technology have significantly improved organizations' proficiency in information retrieval, processing, and decision-making responsiveness (Bustinza et al., 2019; Hu et al., 2021; Shan et al., 2021). Before the pandemic's impacts, the sample enterprises had enhanced their resilience to external shocks through AI technology adoption. SSAW Hotels & Resorts seamlessly incorporated Internet technology into all aspects of hotel operations and management. The customized hotel management systems currently utilized by SSAW Hotels & Resorts encompass the central reservation system, CRM, and PMS, which had achieved large-scale data-driven intelligent management before the pandemic's impacts. Xibei's preemptive adoption of cloud computing before the outbreak enabled the company to rapidly gather external data and market feedback in the face of external shocks and make quick adjustments. As early as April 2018, Xibei closed its offline IDC server room, shifting all core business systems to Alibaba Cloud. This established Xibei as a frontrunner in the digital transformation of the catering industry. After the cloud application, Xibei became the first domestic company that utilized the platform on Alibaba Cloud to independently develop an intelligent supply chain system for the catering industry. Subsequently, Xibei established a joint venture with Magcloud Digital to conduct joint R&D on a new Internet technology-based supply chain system leveraging Alibaba Cloud's infrastructure. In May 2019, the intelligent supply chain system fully replaced the JDE system and became operational. Xibei achieved full-chain digitization and intellectualization in links such as ingredient procurement, central factory, warehouse distribution, and in-store ordering, enhancing the operational efficiency of its stores. Amid the pandemic outbreak, 400 of Xibei's offline stores almost suspended their operations, and only over 100 stores operated based on food delivery services. The company was estimated to suffer a monthly revenue loss of RMB 700-800 million around the 2020 Spring Festival. To rapidly expand its business, Xibei conducted a series of digital initiatives by leveraging its big data analysis abilities and cloud computing resources. (1) Xibei proactively expanded its online food delivery business, with two-thirds of its stores actively participating. This strategy enabled Xibei's food delivery revenue to surpass 80% of its total revenue. Xibei met the essential needs of individual customers by selling hundreds of foods online, including rice, flour, grains, oil, vegetables, and snacks. (2) Xibei embraced the model of enterprise group-buying and meal-ordering to address the dining inconveniences of employees after work resumption. The company introduced "group meal" services, catering to the needs of business clients. Currently, over 90,000 clients have friended Xibei's WeCom, with the service averaging 10,000 orders daily. (3) Xibei built an Internet information service platform that facilitates direct communication between customers and employees, who can share information about malls and products as well as offer food delivery and food ordering services.

AI makes automated decisions and recommendations using all available data, which eliminates the biases inherent in human judgment, and aggregates data to make it comprehensible to people (Colson, 2019). Agrawal et al. (2017) argued, accordingly, that while the cost of this prediction will fall, **human judgment as the other input to decision-making will become more valuable**. AI algorithms, with their capacity to analyze and synthesize voluminous unstructured data, can aid innovators in broadening their search space (Muhlroth & Grottke, 2020), thereby facilitating the exploration of more ideas (Haefner et al., 2021). Although AI is not expected to replace human judgment in selecting meaningful ideas, it can help innovators with their search tasks. By structuring data, it allows ideas to emerge from the interpretation of results. Some ideas might not be recognizable to innovators due to time and resource constraints.

(2) Impact stage: resource allocation and intelligent decision-making

When service enterprises encounter impacts, the ability to adapt and adjust is a critical indicator of organizational resilience. Several factors enable an organization to respond quickly and adjust flexibly: the number of slack resources (Gao et al., 2017), the ability to allocate resources (Huang et al., 2018), effective information sources and strong processing abilities (Linnenluecke, 2017; Sajko et al., 2021; Williams et al., 2017), and the creative and resourceful activities undertaken by management (Williams & Shepherd, 2016).

AI technology adoption has significantly reduced operating costs for service enterprises and enhanced their resource reallocation capabilities at the impact stage. Labor shortage and employees' demand for better benefits and higher salaries have precipitated a swift rise in employment costs, imposing a major constraint on enterprises striving to enhance profits. Against this backdrop, the development of intelligent services has emerged as a pivotal strategy for hotels to save costs and improve efficiency. The application of service robots in the catering and hotel sectors substantially reduced labor costs during the pandemic, which has forged unique selling points for service enterprises and alleviated the financial strain and business crisis faced by some enterprises. As calculated by Guangzheng Hang Seng Advisory, a human waiter takes eight minutes to fulfill a room delivery task whereas a robot can accomplish the same task in just six minutes on average. With both handling a volume of 200 tasks, service robots can save up to 6.7 hours per day. Given the National Bureau of Statistics' disclosure of an average annual salary for hotel employees at RMB 48,260, the average hourly wage amounts to RMB 23.11. By utilizing a robot for service tasks, a hotel can save labor costs of RMB 154.84 per day and about RMB 56,515.5 per year. Furthermore, adopting AI technologies such as facial recognition for authentication and self-service check-in procedures not only decreases hotel operating costs but also provides effective data input conditions for building intelligent decision-making systems. All the sample enterprises actively adopted AI technologies and intelligent identification equipment such as robots to achieve more efficient resource allocation at the impact stage. During the pandemic, Atour Hotel stepped up its digital transformation initiatives for cost reduction and efficiency improvement in its business operations. In terms of customer service, the adoption of automated check-in machines and delivery robots significantly expedited the check-in process and enhanced the efficiency of hotel services. The adoption of digital technologies also reduced redundant personnel and further decreased hotel operational expenses. BTG Homeinns and other hotel groups introduced intelligent “contactless services” such as self-service extension of stays, check-out, and robot delivery. These services not only minimized the risk of viral transmission and cross-infection but also enhanced the service efficiency. In interviews, the senior executive team of BTG Homeinns mentioned that in an environment of uncertainty, robots can be employed to balance human resources, safeguard the well-being of guests and employees, and maintain standardized service levels.

The uncertainty caused by the pandemic is a key motivator for service enterprises to advance their deployment of intelligent robotic services and AI algorithms. AI technology adoption helps service enterprises make discerning decisions during the pandemic, boosting the efficiency and scientific rigor of the decision-making process. From the perspective of internal management, SSAW Hotels & Resorts employed AI algorithms and big data models for predicting customer traffic. By developing detailed member profiles, it conducted more targeted marketing for products and services. For a conglomerate that manages numerous hotels, digital technology offers a valuable tool to manage hotel revenue and enhance hotel operations.

An essential function of AI is to support the decision-making process (Agrawal et al., 2018). AI can sift through extensive datasets to identify underlying patterns and, through meticulous analytical methods, enhance the connection between theoretical frameworks and management practices. Uncertainty serves as a critical boundary condition in formulating decision-making theories. The technical solutions offered by AI mitigate this uncertainty (Alvarez & Barney, 2007), presenting challenges to established theories. AI has transformed the interaction between entities and their surroundings, especially entrepreneurial behaviors within uncertain environments. AI discovers "patterns" by analyzing vast data, thus enabling predictive outcomes. Enhanced precision in predictions significantly diminishes uncertainty (Agrawal et al., 2018). The adoption of AI technologies by sample enterprises during the impact stage of COVID-19 has mitigated the uncertainty imposed by the external environment and enhanced the resource allocation efficiency of service enterprises. It has also improved their ability to process and assess internal information and provided stronger support for management's decision-making in response to external shocks.

(3) Post-impact stage: path exploration and opportunity identification

At the post-impact stage of the pandemic, some service enterprises promptly adopted diversified business strategies to enlarge the pool of shared resources among enterprises and reach cross-industry cooperation with other enterprises. This approach has assisted organizations in recovering from the pandemic, ensuring the stability of organizational structures and performance. The ingenious behavior based on the strategic framework of an enterprise rationally employs internal and external resources (Williams & Shepherd, 2016), balances organizational flexibility and stability (Sajko et al., 2021), and ultimately helps service enterprises attain more sustainable organizational resilience. Specifically, AI technology effectively assists service enterprises in conducting path exploration and encourages them to identify new market entrepreneurial opportunities to achieve rapid growth in new sectors.

AI technology adoption has driven innovation among service enterprises at the post-impact stage. In the post-pandemic era, as people's consumption behaviors and patterns changed, there has been a marked decrease in the demand for business trips. Business travelers increasingly opted for the online model for business communication. The demand for "contactless" services among business travelers has increased, driving the hotel industry to conduct technological upgrades. With the continuous application of technologies, the industry has gradually entered an era characterized by a digital boom. For example, in the exploration of new-generation smart hotel management systems, BTG Homeinns has developed the Wenshu Smart Platform, a property-integrated operations system (PIOS). Leveraging technology empowerment, BTG Homeinns enhances the customer experience and enables guest full-coverage online interaction, boosting the operational efficiency and value of hotels and driving smart hotels to a new development level. Currently, PIOS has been applied to more than 3,300 hotels managed by BTG Homeinns. Its functions include intelligent room control, smart speakers, voice-activated calling, automated air purification, robotic delivery services, self-service check-out, bill settlement and stay extensions, guest feedback systems, live monitoring of hotel restaurant foot traffic, real-time updates on room sanitation and water quality, and integration with the hotel's energy management system.

AI technology is a core element that service enterprises rely on to pursue new entrepreneurial opportunities after external shocks. In industries like catering, high labor costs have long been a tricky issue. The adoption of AI technologies not only helps reduce long-term labor expenses but also ensures product standardization and cleanliness. After suffering from the pandemic's impacts, Xibei made breakthroughs in traditional catering industry practices and invested a lot in ready-to-cook meals by leveraging advancements in AI technologies. The ready-to-cook meal sector has seen the introduction of numerous robotic devices to substitute the considerable labor previously needed for cooking, presenting an opportunity to significantly reduce operational expenses in the catering industry. The core business model for ready-to-cook meals entails logging each customer's eating habits and preferences in a database utilizing big data and cloud computing so that customers receive more personalized services on their next visit. It also involves employing algorithms for targeted marketing to recommend different meals to targeted customer groups. Apart from ready-to-cook meals, Trip.com Group's launching of the "Xiecheng Wendao" large vertical model marks a disruptive innovation in the tourism sector. AI technology adoption is expected to greatly enhance efficiency and user experience in the tourism industry, propelling it into a new development phase. Fueled by the large vertical model, the tourism industry will embrace transformative changes. Users will benefit from more personalized and accurate travel recommendations. The Xiecheng Wendao vertical model is designed to customize travel itineraries that cater to individual preferences and requirements, combining a wealth of tourism data to provide more considerate services. The initial hotel word-of-mouth list on Trip.com has achieved a 70% penetration rate, a 60% in-depth browsing rate, and an 82% recommendation rate. This indicates that more than 70% of Trip.com's users have checked the list, with 60% of them attracted by at least one hotel on the list. Over 80% of users who have viewed the list will recommend it to their friends. The newly released itinerary list on Trip.com has decreased the user decision-making time by 27%, from nine to 6.6 hours. Word-of-mouth lists of destinations and attractions are estimated to provide inspiration for more than 30% of travelers before they start their trips. Moreover, AI technology adoption will accelerate digitization and intellectualization transformation in the tourism industry. AI assistants can offer real-time support to users from pre-sales to after-sales links, resolving issues, providing instant navigation and recommendations, and facilitating more convenient travel experiences. With the help of AI, an average of over 10,000 hours of working time per day is saved for customer service at Trip.com, which is equivalent to freeing up the labor of more than 1,000 customer service staff members each day.

AI technologies can help identify and cultivate new entrepreneurial opportunities. AI is pioneering an innovative playbook that utilizes extensive datasets and learning algorithms to accurately predict phenomena. As such, it is reasonable to assume that these data sets and algorithms can be utilized in identifying and exploring entrepreneurial opportunities. The novelty of these AI systems for innovative search processes lies in their capacity to discern patterns or nuances within data that may elude human detection. AI algorithms, with their capacity to analyze and synthesize voluminous unstructured data, can aid decision-makers in broadening their search space (Muhlroth & Grottke, 2020), thereby facilitating the exploration of a wider array of ideas (Haefner et al., 2021). During the phase of routine pandemic prevention and control, domestic tourism demand has surged, with users' consumption scenarios and habits undergoing profound changes. Short-distance trips and personalized itineraries have emerged as new travel trends. This sets higher requirements for the development of destination tourism. Trip.com, utilizing its Internet platform, has initiated the Ctrip Holiday Farm Project, which is entirely based on data gathering and analysis of rural tourist destinations across China. The project requires the application of AI algorithms to evaluate various factors, including transportation, regional industries, culture, tourist consumption habits, and culinary preferences, for optimal site selection. Before the implementation of a farm project, the trial of a concept typically involves innovators engaging with target customer groups to gather feedback (Sawhney et al., 2005). The access to abundant customer data enables the use of AI's predictive capabilities to assess the value of tourist destinations based on specific objectives (estimated revenue, market suitability, or consumer acceptability). Ctrip Holiday Farm has gained market recognition for its successful implementation. Despite the pandemic, the project's 21 farms managed to become profitable, laying a strong foundation for Trip.com's future growth and enhancing its organizational resilience to navigate risks. AI algorithms significantly enhance the ability of individuals and organizations to search for and spread information. This transformation has facilitated cross-disciplinary and cross-industry communication, fostering high-quality entrepreneurial opportunities with innovation. The impact of AI on uncertainty boundaries has altered the traditional opportunity identification process (Shane & Venkataraman, 2000).

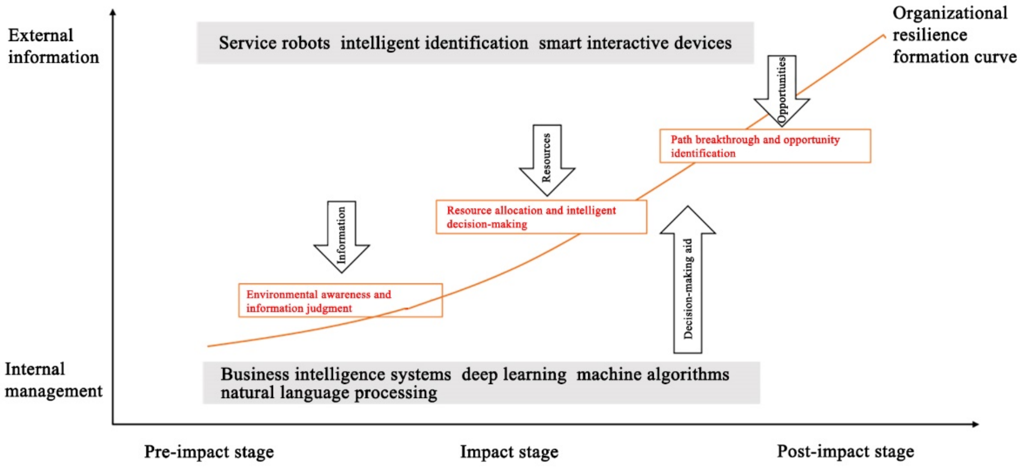

Figure 4.1 Three-stage Model of AI Technology Adoption and Organizational Resilience Formation

Based on the aforementioned case study, this study has developed a three-stage model for AI technology adoption and organizational resilience development (see the figure below). In-depth research and literature review concerning five sample enterprises reveal that service enterprises have undergone three stages in utilizing AI technology to manage the pandemic's impacts. Moreover, the mechanism by which AI technology functions varies across different stages of external shocks. This study delineates the distinct mechanisms through which various AI technologies facilitate external information acquisition (primarily via service robots, intelligent recognition, smart interactive devices, etc.) and internal management support (mainly through business intelligence systems, deep learning, machine algorithms, natural language processing, etc.): (1) At the pre-impact stage, service enterprises adopted AI technologies to enhance their external environmental awareness and evaluate pertinent information, strengthening their confrontation capability; (2) At the impact stage, service enterprises utilized AI technologies to build resource advantages and reduce operational expenses in response to changes in the environment; (3) At the post-impact stage, AI technologies were adopted by service enterprises to improve innovation abilities, identify new possibilities in the external market, and enhance industry dominance and resilience to future risks.

4.5 Comparative Analysis: Operational Performance of Service Enterprises with and without AI Technology Adoption

To emphasize the impact of AI applications on organizational resilience and coping with external environmental shocks in service enterprises, this study conducted a comparative analysis and case studies. By doing so, it further compared the operational performance of service enterprises using AI technologies with those that do not. By using data from publicly listed companies and case studies, this study examined the robustness of its conclusions.

4.5.1 Comparative analysis

This study compared the outcomes arising from the adoption of AI technologies by listed service enterprises and categorized these enterprises into two groups based on whether they had adopted AI technologies (group 1 comprises service enterprises that have adopted AI technologies, while group 0 includes those that have not). The number of samples in group 1, which corresponds with the sample size for sub-study 1, is 1,937, whereas group 0 contains 1,376 samples. It evaluated nine fundamental operating indicators, including the debt ratio, ROA, sales revenue, current ratio, the proportion of independent directors, management shareholding ratio, the proportion of R&D personnel, R&D investment, and innovation capability. The specific results are shown in Table 4.3.

Table 4.3 Comparative Analysis

	Group1			Group0			Group1-Group0		
Variable	**Sample size**	**Mean value**	**Variance**	**Sample size**	**Mean value**	**Variance**	**F value**	**Chi ^{2}(1)**	**P>Chi**
ROA	1,937	.042	.085	1,376	.039	.093	1.10	16.258	.000
Debt ratio	1,937	.406	.189	1,376	.421	.191	5.15	60.087	.000
Sales revenue	1,937	$1.30e^{10}$	$6.60e^{10}$	1,376	$1.09e^{10}$	4.21e10	1.12	299.697	.000
Current ratio	1,937	2.715	3.164	1,376	2.354	2.333	12.91	141.968	.000
Proportion of independent directors	1,925	.382	.058	1,376	.379	.055	1.23	3.292	.000
Management shareholding ratio	1,895	.185	.585	1,341	.180	.205	.11	1,600	.000
Proportion of R&D personnel	1,937	21.712	15.379	1,224	16.305	12.084	107.34	82.041	.000
R&D investment	1,937	$4.23e^{8}$	$1.51e^{9}$	1,250	$2.75e^{8}$	1.05e9	9.19	186.706	.000
Innovation capability	1,845	.241	.168	1,224	.180	.132	113.73	81.246	.000

Performance indicators include three variables: ROA, debt ratio, and sales revenue. This study compared the above-mentioned key operating indicators between two groups of listed service enterprises: Group 1, which has adopted AI technologies, and group 0, which has not. The findings reveal that group 1 demonstrates significant advantages in these performance indicators compared with group 0. (1) In terms of ROA, group 1 significantly outperforms group 0 ($p <.01$). This is mainly because AI technology adoption enhances enterprises' operational efficiency and optimizes resource allocation, thereby boosting profitability. AI technologies facilitate more accurate data analysis and forecasting, enabling enterprises to seize market opportunities more effectively, enhance the quality of their products or services, and increase sales revenue and profits. (2) Concerning the debt ratio, group 1 has a significantly lower mean value compared with group 0 ($p <.01$). It indicates that enterprises adopting AI technologies manage debt risks more effectively and maintain healthier financial conditions. AI technologies assist enterprises in achieving more precise financial management, optimizing cash flows and liability structures, and diminishing financial risks. (3) Regarding sales revenue, group 1 also registers a higher mean value, significantly surpassing that of group 0 ($p < .01$). This is largely attributed to the adoption of AI technologies in marketing and sales. AI technologies enable the creation of precise user profiles and personalized recommendations, allowing enterprises to meet customer needs more accurately, enhance customer satisfaction and loyalty, and boost sales revenue.

The indicators for resources and organizational structure encompass three variables: current ratio, the proportion of independent directors, and management shareholding ratio. Compared with service enterprises that do not adopt AI technologies (group 0), those adopting AI technologies (group 1) exhibit significant advantages in these indicators, namely a higher current ratio, a greater proportion of independent directors, and a larger management shareholding ratio. (1) The current ratio is a crucial metric for assessing an enterprise's short-term solvency. Enterprises adopting AI technologies (group 1) typically exhibit a higher current ratio, and the disparity between the two groups is quite pronounced ($p < .01$). This is because AI technologies enable enterprises to predict and manage their cash flows with greater precision, ensuring their capacity to repay debts in the short term. AI technologies enhance enterprises' efficiency of capital operations and reduce liquidity risks through optimized inventory management and receivable recovery. (2) The proportion of independent directors is significantly higher in group 1 than in group 0 ($p < .01$). This may indicate that enterprises adopting AI technologies pay more attention to standardization and transparency in their corporate governance structures. Introducing more independent directors helps enhance the fairness and objectivity of enterprise decision-making processes and the overall governance quality. Moreover, AI technology adoption may require introducing more professional independent directors to supervise and guide the strategic development of the enterprise. (3) From the perspective of management shareholding ratio, group 1 also displays a notably higher ratio ($p < .01$). This may result from the fact that enterprises adopting AI technologies emphasize consistency between the management's and the enterprise's long-term development goals. Increasing the management shareholding ratio can boost the management's work enthusiasm and sense of responsibility, compelling them to concentrate on the enterprise's long-term interests. Additionally, as the performance of enterprises adopting AI technologies may be more reliant on the management's decision-making and implementation capabilities, increasing the management shareholding ratio represents a reasonable incentive mechanism.

Innovation indicators include three variables: the proportion of R&D personnel, R&D investment, and innovation capability. Service enterprises adopting AI technologies (group 1) enjoy huge advantages in the proportion of R&D personnel, R&D investment, and innovation capability compared with those that do not adopt AI technologies (group 0). (1) Concerning the proportion of R&D personnel, group 1 has a significantly higher mean value than group 0 ($p < .01$). This is due to the need for professional R&D teams to adopt AI technologies, including roles such as data scientists, algorithm engineers, and software developers. These R&D personnel are responsible for designing, developing, and optimizing AI systems to meet the enterprise's business requirements. As a result, enterprises adopting AI technologies tend to invest more in their R&D personnel to maintain the technical team's professionalism and competitiveness. (2) Regarding R&D investment, group 1 demonstrates a higher level compared with group 0 ($p < .01$). The R&D of AI technologies requires substantial funds and resources for equipment purchases, software development, and testing and verification. Enterprises adopting AI technologies usually have clear R&D plans and allocate sufficient funds to support the implementation of these plans. The continuous R&D investment enables enterprises to maintain their technological advantages and keep developing innovative products and services. (3) In terms of innovation capability, group 1 also possesses significant advantages over group 0 ($p < .01$). The application of AI technology itself is a form of innovation. It can help enterprises break free from traditional constraints, achieving optimization and innovation in business processes. With the adoption of AI technologies, enterprises can develop more intelligent and efficient products and services, enhancing the user experience and their competitiveness. Furthermore, the expertise of R&D personnel and the rise in R&D investment help enterprises cultivate their innovation abilities and foster sustainable development.

4.5.2 Case analysis

From 2020 to 2022, under the impact of COVID-19, most service enterprises experienced profit decline and business contraction, and some even faced survival threats. Take the catering industry as an example. As of December 31, 2022, a total of 519,000 catering-related enterprises had been deregistered or revoked. Most enterprises that could not sustain operations ran traditional operating models before the pandemic and had not yet incorporated digital technologies like AI to support their growth.

Based on heterogeneity analysis, this study employed case data from two enterprises that suffered losses during the pandemic as a comparative framework against those that remained profitable during the same period. This comparison underscores the importance of AI technologies in assisting enterprises to respond to external shocks.

(1) Huatian Hotel Group Co., Ltd.

Huatian Hotel Group Co., Ltd. is a cross-regional comprehensive modern service enterprise mainly engaged in the hotel service industry, and it is controlled by Hunan Yangguang Huatian Tourism Development Group Co., Ltd. The company was listed on the Shenzhen Stock Exchange in 1996. The company's hotel brands include Huatian Hotel, Huatian Holiday Hotel, Huatian Choice Hotel, and more, featuring about 40 self-operated and franchised hotels. The company's first high-star-rated hotel, Hunan Huatian Hotel, welcomed its first guests on May 8, 1988. It has been awarded the Five Star Diamond Brand, Famous Trademark of China, National Corporate Culture Demonstration Base, and Advanced Collective in National Tourism System. Over the years, it has maintained a place on the "Top 60 Hotel Groups in China" and "Top 300 Hotel Groups in the World" rankings.

Affected by the pandemic, the company experienced huge operational challenges in the first half of 2020. During this period, the net profit attributable to the shareholders of the listed company recorded a loss of RMB 200-240 million. Despite a year-on-year increase of 78.07% in operating revenue in the first half of 2021, the company still incurred a net loss of RMB 154 million. In 2022, the company's operating revenue fell to RMB 474 million, a decrease of 20.29% compared with the previous year. Specifically, the hotel business' operating revenue dropped by 23.16% year on year to RMB 419 million, and the net profit attributable to the listed company's shareholders suffered a loss of RMB 310 million. As of 2023, the company had not emerged from the shadow of these losses, continuing to face considerable operational challenges.

For all players in the hotel industry, the pandemic has prompted travel restrictions and a decline in consumer confidence around the globe, culminating in a sharp decrease in demand for hotel services. As a leader in the hotel service industry, the company has been unavoidably affected by this downturn. Moreover, the company implemented measures such as suspending guest reservations in pandemic-stricken regions and strategically halting operations in some hotels to adhere to pandemic prevention protocols. These measures significantly impacted the company's hotel service operations, causing a sharp decline in revenue. During the pandemic, hotels encountered larger challenges with cost control, changes in market demand, and maintaining good service quality, which exacerbated their risk of suffering losses. Unlike BTG Homeinns, SSAW Hotels & Resorts, and Atour Hotel, which managed to achieve profitability promptly, the company struggled to overcome the pandemic's adverse effects. Apart from the problems in operations, the company did not pay much attention to AI technology adoption.

The adoption of AI technologies in the hotel industry holds huge potential, with application scenarios such as intelligent room management, automated customer service, and data analysis. Adopting AI technologies can greatly enhance the operational efficiency of hotels, reduce operating costs, and improve customer satisfaction. However, the company may have missed these opportunities to bolster its competitiveness by failing to proactively adopt AI technologies. During the pandemic, AI technologies became particularly crucial for the hotel industry, as the pandemic caused drastic changes in customer needs and operational challenges. Hotels equipped with advanced AI technologies could better adapt to such changes and mitigate losses by utilizing data analytics to forecast market demand, streamline service processes, and enhance customer satisfaction. However, the company failed to effectively address these challenges due to the absence of relevant technological support. Furthermore, AI technologies can enhance a hotel's risk management abilities. Hotels with intelligent early warning and decision-making support systems can respond more quickly to emergencies such as a pandemic and curtail losses. The lack of AI technology adoption in advance by the company might result in shortcomings in risk management, thereby exacerbating its financial losses.

(2) Nanhu Travel

Established in 1999, Nanhu Travel has managed numerous branches across the country, with over 120 branches located in Guangdong Province alone. Upon its listing on the National Equities Exchange and Quotations (NEEQ), the company's market value nearly reached RMB 2 billion. Its "West Holiday" brand is recognized as the earliest and most successful tourism brand in Guangdong that specializes in travel experiences in western China. Guangdong Nanhu International Travel Service Co., Ltd. was established in 2005. Leveraging the appeal of low-cost tourism to attract many customers, Nanhu Travel started to expand its market share. In 2013, it ranked ninth in the annual list of Top 10 Travel Agencies in China, an election organized by the Ministry of Culture and Tourism of the People's Republic of China. The company enjoyed various resources, including scenic spots, hotels, and fleets, and had about 2,000 employees. In 2016 when the NEEQ offered favorable policies, Nanhu Travel seized the opportunity to raise funds, securing RMB 220 million through the listing of its subsidiary, Foshan Nanhu International Travel Service Co., Ltd., on the NEEQ. In the first year of listing, Nanhu Travel achieved revenues of RMB 2.008 billion, marking a year-on-year increase of 161.92%. The net profit attributable to shareholders of the listed company reached RMB 49.0795 million, generating a year-on-year surge of 485.44%. Due to the pandemic, a large number of customers canceled their orders placed at Nanhu Travel, putting huge pressure on Nanhu Travel's cash flow. When the pandemic broke out in 2020, it was reported that Nanhu Travel defaulted on payments for staff wages and tour group expenses. Currently, Nanhu Travel is still facing severe financial hardships, including significant arrears, and is on the verge of bankruptcy.

From the perspective of business scale, Nanhu Travel is a typical mid-range enterprise. It has achieved a notable business scale and is recognized as a leader in the outbound tourism wholesale sector. Nanhu Travel's substantial number of employees and high fixed costs for operating the existing business became a considerable encumbrance during the pandemic. If Nanhu Travel solely relies on business transformation in domestic urban vacations and short-distance rural tourism, it cannot recapture its pre-pandemic business scale. Travel agencies often have few fixed assets. As an asset-light enterprise, Nanhu Travel finds it challenging to obtain credit or policy support. In addition, the fact that unqualified travel agencies engage in low-price competition has exacerbated the difficulties faced by mid-range enterprises. For instance, in the first half of 2021 when the pandemic seemed to be under control, the market saw the exit of several qualified travel agencies and the emergence of unqualified ones. These new entrants engaged in low-price competition and resulted in a disorderly tourism market. Hence, addressing the issues of low-cost tourism and unauthorized operations became the tourism industry's focus during that period. Another significant factor contributing to Nanhu Travel's verge of bankruptcy during the pandemic was its failure to fully plan and adopt AI technologies. For instance, utilizing an intelligent customer service system could have enabled Nanhu Travel to promptly address customer inquiries and enhance customer satisfaction. Moreover, through data analysis, it could have precisely identified target customer groups and developed more effective marketing strategies. However, Nanhu Travel, which did not equip itself with AI technologies, could not capitalize on these advantages, potentially leading to larger losses from inefficient operations and poor service quality.

AI technology is a means to cut costs and enhance production efficiency (Amabile, 2019; Cockburn et al., 2018). It can lower enterprises' operating costs through automation and offer personalized and targeted services to customers, thereby significantly enhancing service efficiency and quality (Samara et al., 2020). In the face of the impacts brought on by the COVID-19 pandemic, the hotel and tourism industries undeniably suffered significant blows. The key to survival during these harsh times lies in a company's ability to leverage technology and effective management to increase efficiency and reduce costs. AI technology can automate and optimize workflows in the hotel and tourism industries. For example, an automated guestroom management system allows hotels to instantly refresh room statuses, reducing the burden on the front desk and housekeeping center. Meanwhile, an intelligent reservation system can automatically manage customer bookings, diminishing the likelihood of manual errors and accelerating processing speed. Huatian Hotel Group carried a significant amount of fixed operating expenses, including rent, equipment depreciation, and staff wages. These expenses remained unchanged even with a decline in revenue. The company also channeled more resources into pandemic-prevention measures, which included procuring pandemic-prevention supplies, conducting routine sanitization, and reinforcing staff training. These additional pandemic prevention expenses increased the company's operational costs. Failing to effectively reduce costs, the company found itself gradually weighed down by escalating costs. From the standpoint of customers and tourists, intelligent customer service, precise information push, robot sensing services, and other methods profoundly influence their needs, preferences, decision-making, and experiences (Ivanov & Webster, 2017). An intelligent customer service system, powered by natural language processing and machine learning technologies, can provide real-time and accurate responses to customer and tourist inquiries and offer personalized services. This aligns well with consumers' needs for efficient and convenient services, enhancing their experiences. Intelligent customer services can deliver quick responses to needs such as inquiring about the order status, seeking product details, and addressing after-sales issues, ensuring that consumers receive satisfactory solutions promptly. The precise information push technology can facilitate customized content and promotions based on consumers' historical behaviors, interests, and preferences. This convenience makes it easier for consumers to discover products and services that capture their interest and helps them make more informed decisions. As a traditional tourism enterprise, Nanhu Travel primarily employed manual customer services to communicate with tourists. This approach required significant human capital expenditure. During the pandemic, dwindling revenue and substantial wage expenses posed challenges to Nanhu Travel's business operations. Furthermore, the efficiency of manual inquiries and responses was relatively low. The pandemic made it challenging for the manual service model to promptly adapt to tourists' changing travel requirements. When international tourism came to a halt, other travel needs of tourists failed to be met promptly. Nanhu Travel's core business activities nearly came to a standstill, leading the company to the verge of bankruptcy. AI adoption in production is mainly realized through robots, which predominantly perform a series of repetitive tasks requiring low technical expertise. The application of robots substitutes human labor in certain stages, effectively reducing production costs. This substitution promotes mechanization and automation in the production cycle and enhances production efficiency (Acemoglu & Restrepo, 2019). Furthermore, investment in robots not only establishes immediate production benefits but also fosters long-term capital growth. This further catalyzes technological advancements and enhances the productivity of machines in existing automated tasks, thereby facilitating long-term productivity growth (Acemoglu & Restrepo, 2018a; L. Li et al., 2021). Digital transformation holds significant importance for the hotel industry, as it introduces hotel robots that can help reduce costs and improve efficiency. While collaborating with human staff, robots can solve human labor-related problems and facilitate intelligent pandemic prevention. By implementing a robotic concierge system for online ordering, and utilizing hotel delivery robots for automated pick-up and drop-off operations, hotels can not only offer disposable items but also provide various valuable goods, thereby increasing additional profits for the hotels.

Big data and AI technologies are driving forces of fundamental shifts in organizational management and business logic. While AI technology does not radically overturn existing organizational structures (Brock & Wangenheim, 2019), it exerts a considerable influence on organizations' operating models and enterprises' boundaries. In terms of operational models, AI technology optimizes various aspects such as production, sales, and services through automation and smart approaches. This allows organizations to respond more effectively and accurately to market demand, boosting operational efficiency and reducing costs. Simultaneously, AI technology also aids enterprises in the real-time analysis and prediction of data, enabling them to make more informed decisions and enhance their competitiveness in the market. The adoption of big data and AI technology has shattered the confines of traditional industries, fostering cross-industry and -field cooperation and innovation. This enables enterprises to adjust their business structures more flexibly, expand new market segments, and pursue diversified development. The openness and shared nature of AI technology facilitate information exchanges and resource integration among enterprises, further enhancing their development potential. Huatian Hotel Group and Nanhu Travel are representative enterprises in the hotel and tourism industries. However, they continue to operate under the traditional high-cost and labor-intensive model, which can hardly adapt to the ongoing trend toward digitization and intellectualization. With the development of technology, the hotel and tourism industries are progressively embracing digital transformation. By leveraging technologies such as big data and AI, these sectors are enhancing operational efficiency and service quality. Huatian Hotel Group and Nanhu Travel rely too much on experience and practices for their operations. Their relatively low acceptance of new technologies and models, as well as their greater emphasis on short-term performance and profits, overshadow a commitment to long-term digital and intelligent transformation. Digital and intelligent transformation usually necessitates substantial investment in technology, including software and hardware, system development and maintenance, data analysis, and AI adoption. This requires the enterprise management to promptly apprehend market development needs and engage in proactive planning. Before and during the pandemic outbreak, the senior management of Huatian Hotel Group and Nanhu Travel failed to make plans for AI technology adoption. Consequently, they encountered challenges in transforming operating models and found their business models lagging behind those of their peers. Before the outbreak of the pandemic, despite the widespread attention and application of AI technology globally, it appears that the top management of Huatian Hotel Group and Nanhu Travel did not give it adequate consideration. They possibly concentrated more on upholding traditional operating and business models, believing in their stability and not seeing the need for significant changes. However, when the pandemic suddenly broke out, the models encountered unprecedented challenges. Due to pandemic-related restrictions and diminished customer inclination to travel, the hotel and tourism sectors experienced a drastic reduction in business volume, subjecting enterprises to intense operational pressure. In this case, the traditional models of Huatian Hotel Group and Nanhu Travel proved ineffective in responding to market changes. Against this backdrop, the advantages of AI technology began to manifest. Enterprises can leverage AI technology to learn about market demand more precisely, optimize products and services, and enhance customer experiences. The technology can also assist enterprises in reducing operating expenses and improving operational efficiency, thereby equipping them to meet the challenges posed by the pandemic. Nevertheless, Huatian Hotel Group and Nanhu Travel faced difficulties in operating model transformation and business model backwardness because their senior management did not plan AI technology adoption before and amid the pandemic. Due to the lack of relevant technological reserves and talent support, they were unable to swiftly introduce and implement AI technology, placing their enterprises at a disadvantage in the market competition. During the pandemic, the traditional high-cost and labor-intensive model proved to be particularly uneconomical. Inadequate technical reserves and a lack of talent support resulted in a slow transition and unfavorable outcomes for Huatian Hotel Group and Nanhu Travel. In the era of digitization and intellectualization, enterprises must stay abreast of contemporary trends and actively adopt new technologies to remain invincible in the intense market competition.

5. Conclusion and Outlook

5.1 Research Summary

Grounded in practical and theoretical contexts, this study focuses on a key research question: How does AI technology adoption affect the organizational resilience of service enterprises? Employing empirical research and case study analysis, it delved deeply into the mechanisms of influence and process models through which AI technology adoption affects the organizational resilience of service enterprises.

Through the empirical analysis of second-hand data, sub-study 1 reveals that AI technology adoption exerts a positive effect on organizational resilience. AI technology adoption enhances both high-liquidity and low-liquidity slack in service enterprises and indirectly bolsters organizational resilience via increased high-liquidity slack. The diversification strategy and scale of service enterprises play a negative role in adjusting the impact of AI technology adoption on high-liquidity slack resources. The research findings indicate that AI technology adoption can directly enhance the organizational resilience of service enterprises and indirectly enhance it by amplifying the high-liquidity slack in these enterprises.

Through the study of five case enterprises, sub-study 2 reveals that AI technology adoption of service enterprises to mitigate the pandemic's impact (primarily from the beginning of 2020 to the end of 2022) progressed through three stages. The mechanism through which AI technology exerts its influence varies across different stages of external shocks. At the pre-impact stage, service enterprises adopted AI technologies to enhance their environmental awareness and the ability to evaluate pertinent information, strengthening their confrontation capability. At the impact stage, service enterprises utilized AI technologies to build resource advantages and reduce operational expenses in response to changes in the environment. At the post-impact stage, AI technologies were used by them to improve innovation capabilities, identify new possibilities in the market, and enhance industry dominance and resilience to future risks. During the pandemic, service enterprises employed AI technologies to cultivate organizational resilience at pre-impact, impact, and post-impact stages. This allowed them to respond to the pandemic's impacts, maintain stable operations, and establish the groundwork to address potential challenges in the future. Sub-study 2 conducted an in-depth comparative analysis. It reveals that service enterprises utilizing AI technology far outperform those that do not in nine fundamental operational capability indicators. They are return on assets (ROA), debt ratio (as a negative indicator), sales revenue, current ratio, the proportion of independent directors, management shareholding ratio, the proportion of R&D personnel, R&D investment, and innovation capability. Additionally, the study employed two negative cases to validate the crucial role of AI technology adoption in enhancing the organizational resilience of service enterprises.

This study leveraged various research steps and methods, including literature review, theoretical model building, case study, and fixed effects model. The findings from the empirical research and case studies address the central research question, "How does AI technology adoption affect the organizational resilience of service enterprises?"

5.2 Research Contributions

(I) Theoretical contribution

This study potentially contributes to theoretical knowledge in the following ways:

Firstly, it confirms the mechanism by which AI technology adoption influences organizational resilience, identifying important antecedents of organizational resilience. Through empirical research, this study verifies the positive influence of AI technology adoption on the organizational resilience of service enterprises. Additionally, it delves into the indirect pathway of influence of AI technology adoption through high-liquidity slack. This study reveals that AI technology adoption is an important antecedent to organizational resilience. Past research has touched on how slack resources can aid in fostering organizational resilience. Yet, they have not distinguished between the impacts of different slack resources, nor have they highlighted the essential antecedents of these resources within the framework of digital transformation. This study focuses on AI technology, which is a crucial digital technology widely used in service enterprises. While there are existing practical cases demonstrating how AI technology adoption aids enterprises in coping with external shocks, academia has not yet investigated whether the adoption affects organizational resilience. This study bridges this theoretical void and contributes to research on the antecedents of organizational resilience.

Secondly, it sheds light on the effects of AI technology adoption on various slack resources within service enterprises and their marginal conditions. By validating the impact model of AI technology adoption on the organizational resilience of service enterprises, this study discerns the influence of AI technology adoption on diverse slack resources within service enterprises. Also, it further contributes to research on the effectiveness mechanism of AI technology adoption. Existing studies have explored the influence of AI technology on organizational structure, enterprise innovation, and management decision-making, but have overlooked the significance of AI technology as a pivotal means for service enterprises to develop essential slack resources. This study, therefore, discovers that AI technology can enhance high-liquidity and low-liquidity slack within enterprises. It also investigates the marginal conditions affecting the efficiency of AI technology, namely the moderating effects on enterprise scale and business diversification, thus enriching the research on the efficiency mechanisms of AI technology.

Thirdly, the study establishes a process model illustrating how AI technology adoption assists service enterprises in cultivating organizational resilience. Through in-depth investigation and analysis of representative service enterprises, this study constructs a process model illustrating how AI technology adoption aids in developing organizational resilience within service enterprises, enriching the research on the processes involved in organizational resilience. AI technology adoption assists enterprises in detecting potential external shocks at the pre-impact stage. It leverages various information to allocate resources and quickly assess the effectiveness of enterprises' decisions in response to shocks at the impact stage. Moreover, it innovates and identifies new entrepreneurial opportunities at the post-impact stage.

(II) Practical suggestions

This study finds that AI technology can foster organizational resilience in service enterprises, aiding them in their response to external shocks. In the future, service enterprises should make full use of emerging digital technologies, including AI, to enhance their decision-making abilities. For example, service enterprises can leverage AI technology for data analysis and prediction. By processing vast datasets, AI can offer various data analysis and prediction functions. This enables senior management teams of enterprises to gain a deeper understanding of market demand, competitive landscape, and industry trends, allowing them to develop more informed strategies and decisions quickly. Besides, service enterprises can adopt AI technologies to provide automated and intelligent support for decision-making. AI technologies can streamline repetitive and low-value-added tasks such as financial accounting, contract reviews, and risk assessments with automation and smart solutions. This will help save human resources and enhance decision-making efficiency and accuracy. Furthermore, through technologies like machine learning and natural language processing, AI can give more targeted decision support, assisting enterprises' senior management teams in data and trend interpretation to improve decision-making quality. Moreover, service enterprises can utilize AI technologies to fuel innovation and strategic planning. By simulating and optimizing complex, innovative, or strategic management issues like market forecasting, product design, and marketing strategies, AI technology can boost enterprises' competitiveness and creativity. Overall, AI technology can provide more comprehensive, timely, and accurate data support and insights into the decision-making process of senior management teams of service enterprises, thus improving their decision-making efficiency and accuracy. Meanwhile, AI contributes to saving human resources and enhancing decision-making security through automation and intelligent technologies. In the implementation of decisions, AI can offer more accurate communication and interaction methods to help enterprises improve service quality and brand image. Nevertheless, it is essential to emphasize that the adoption of AI technology should align with the actual situations of enterprises to prevent blind emulation and the creation of redundant technologies. This ensures the effectiveness and feasibility of the technologies. Attention should also be paid to the ethics and privacy issues brought by AI technology, to protect enterprises' and individuals' legitimate rights and interests.

5.3 Limitations and Prospects

This study investigates the relationship between the adoption of AI technology by service enterprises or those in the tertiary industry and organizational resilience. While the findings exhibit a degree of generalizability, their applicability may vary across different types of enterprises due to unique industry characteristics. Sub-study 1 contends that service enterprises exhibit pronounced characteristics of slack resources. This is evident as these enterprises often encounter slack resources due to the seasonal nature of their operations and large-scale fixed-asset investments (Liu Bing, 2015). Hence, the link between AI technology adoption and organizational resilience enhancement via the mobility of slack resources is more obvious in service enterprises. In other industries, AI technology adoption may affect organizational resilience through alternative pathways. Further research might include industry-wide sampling or investigating various pathways and contexts of AI technology adoption across different industries.

This study does not take into account all contextual factors. Sub-study 1 focuses on the moderating effects of business diversification and enterprise scale, underscoring how enterprise heterogeneity influences the positive effect of AI technology adoption on liquidity slack. However, factors such as an enterprise's external environment and the unique attributes of its senior management team can also affect the effectiveness of AI technology adoption. Notably, it is believed that the differences in senior management teams will affect enterprises' decision-making processes (Hambrick & Mason, 1984). Currently, AI based on deep learning algorithms is like a black box because the intermediate processes through which managers get output results from specific inputs are uncontrollable. Relying solely on advancements in AI technology is insufficient to address intricate problems in a complex society. A human-machine integrated decision-making system must integrate the diverse experience of management teams and higher decision-making efficiency. Senior management teams with more diverse backgrounds are better equipped to tackle more intricate information processing tasks, thereby aiding in the effective utilization of AI technology for functions such as resource allocation and cost reduction. Hence, future research endeavors can contemplate additional contextual factors within and outside enterprises, with particular attention to the features of senior management teams and their impact on the effectiveness of AI technology adoption.

They can also delve deeper into the effects of the adoption of different AI technologies on organizational resilience. While sub-study 2 touches on the practical application of various AI technologies within enterprises, it fails to distinguish the specific types of AI technologies used by different enterprises and the varied efficiencies they may generate. For instance, as a critical area of AI, machine learning has garnered academic interest for its influence on organizational management (J. Liu et al., 2023). By analyzing historical data and experience, machine learning can create statistical models that draw from the relationships between internal and external variables in an enterprise, forecasting the potential effects of diverse strategic adjustments in response to external shocks (Grimmer et al., 2021). Subsequent research can focus on the features and essence of machine learning to further explore the specific mechanisms through which AI technologies impact organizational resilience.

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[Appendix]

Interview Outline for the Research on the Impact of AI Technology Adoption on Organizational Resilience of Service Enterprises

1. Please describe your role within the enterprise and your primary business responsibilities.

2. Could you detail your enterprise's operations before the COVID-19 outbreak in 2020?

3. Before the pandemic, what AI technologies did your enterprise utilize, in which business segments, and what results were achieved?

4. Please describe in detail how the pandemic has affected your enterprise since 2020.

5. What was the biggest challenge your enterprise faced during the pandemic, and how did it address these difficulties? (For more information: specific details of the pandemic's impact on each business segment, changes in the enterprise's strategies, and corresponding results)

6. What role did digital technology, particularly AI, play in your enterprise's response to the pandemic? (For more information: adjustments in the enterprise's digital strategy post-pandemic, the role of AI technology before, during, and after the pandemic's impact, and the improved abilities within the enterprise)

7. Please talk about your enterprise's follow-up planning for AI technology adoption.

Note: The interview content should suit the specific industry conditions of sample enterprises.