J. Electrical Systems 20-3 (2024): 246-262

[1]Weiwei Dong

[2]*Xinye Fan

Research on the Influence Mechanism of Artificial Intelligence Capability on Ambidextrous Innovation

Abstract: With the continuous development and widespread adoption of artificial intelligence (AI) technology, enterprises have realized the importance of possessing artificial intelligence capabilities to enhance organizational performance. However, there is still a relative lack of empirical research on how to build AI capabilities, and how AI capabilities impact organizational innovation performance. Based on the resource-based theory, this study constructs a conceptual model of "AI Capabilities - Organizational Response (Organizational Learning and Organizational Agility) - Ambidextrous Innovation", exploring the direct impact of AI capabilities on ambidextrous innovation, and the mediating effects of organizational learning and organizational agility, also the moderating role of digital strategy in this linkage. With data from 253 survey questionnaires of Chinese enterprises, the results indicate that: first, AI capabilities have a significantly positive impact on organizational ambidextrous innovation; second, organizations with high levels of organizational learning ability and agility can better leverage AI capabilities to promote the development of ambidextrous innovation; Thirdly, digital strategy has played an active role in regulating the influence path of two-way innovation within the organization and provided sufficient boundary conditions; fourth, The data capability, technological capability, and fundamental resource capability of AI capabilities have differentiating effects on exploratory and exploitative innovations. The findings of this research hold significant theoretical and managerial value for understanding the driving mechanisms of organizational innovation performance in the era of AI.

Keywords: AI capability, ambidextrous innovation, organizational learning ability, organizational agility

I. Introduction

The scale of global artificial intelligence industry is growing rapidly with a compound growth rate of over 30%, which has increased from $690 billion in 2017 to $3 trillion in 2021, and is expected to exceed the $6 trillion mark in 2025 [1]. The emergence of ChatGPT has brought great potential commercial value. However, the 2020 research report of Boston Consulting Group (BCG) found that only 10% companies reported that their investment in artificial intelligence had achieved significant returns [2]. Most enterprises still face a series of obstacles when using artificial intelligence, and cannot fully use artificial intelligence to empower enterprises, and the lack of artificial intelligence capability is regarded as the main implementation challenge [3]. Many cutting-edge researches focus on the importance of artificial intelligence. Anton argues that organizations should ensure adequate technical and artificial intelligence expertise [4], invest in appropriate artificial intelligence infrastructure [5]. However, there are still few literatures about analyzing the influence of organizational ability in the application of artificial intelligence. [6-8].

The existing research has paid attention to the influence of artificial intelligence on enterprise innovation. For example, Rammer believes that there is a positive relationship between artificial intelligence and organizational innovation [9]. While there exist some research in the realm of organizational innovation, there is a scarcity of empirical studies concerning the influence of various organizational resources on innovation and the prioritization of resource allocation for development. At present, the literature has not fully studied these problems, and it is still relatively scarce to study the influence mechanism of artificial intelligence capability on Ambidextrous Innovation. Therefore, this paper will deeply explore the mechanism of AI capability in Ambidextrous Innovation and need more in-depth exploration to reveal its influence path and effect on Ambidextrous Innovation. At the same time, at present, few studies have carried out detailed research on the AI capability and discussed its impact. Based on the resource-based theory, this paper adopts the AI capability measurement tool established by Mikalef and Gupta, and divides it into three dimensions [6], to analyze the influence degree and mechanism of various tangible resources obtained by enterprises from the market on organizational innovation.

[1] Associate Professor, Department of Business Administration of School of Economics and Management, Shanghai Institute of Technology, Shanghai, China

[2] School of Economics and Management, Shanghai Institute of Technology, Shanghai, China

*Corresponding author: Xinye Fan

Organizational innovation is not only a resource issue, but also a strategic issue [10]. Enterprises need to plan, coordinate and promote complex pre-innovation preparation, innovation process and post-innovation development issues from a strategic management perspective. Digital strategy not only provides a strong technical foundation for organizational innovation, but also provides strong support for organizational innovation through data-driven decision-making methods. Enable organizations to better understand customer needs, market trends and business performance, and enable them to predict and respond to changes more accurately and make more competitive decisions. Digital strategy plays an important moderate role in organizational innovation. Through the strategic guidance of technology-driven, change-driven, data-driven and personnel training, organizations can realize innovation and competitive advantage in the digital age.

Understanding the impact of AI capabilities on organizational innovation will help organizations keep pace with technological evolution, improve efficiency, reduce costs, optimize existing processes, and uncover new business opportunities and innovative methods. Our research will contribute to determining how to maximize this advantage, providing new insights and frameworks for management and organizational theory, enriching the academic research field. According to the above theoretical and practical background, this paper combs the research results of artificial intelligence capabilities and innovation, and tries to answer the following three questions: (1) The meaning and dimension construction of artificial intelligence capabilities; (2) What is the differential effect of artificial intelligence capabilities on organizational Ambidextrous Innovation? (3) The influence mechanism of artificial intelligence capabilities on organizational Ambidextrous Innovation, and what intermediary and moderating variables are included. Compared with the existing literature, the marginal contribution of this paper can be summarized as follows: (1) We have described in depth how to build the artificial intelligence capabilities and the practice of developing artificial intelligence; (2) Reveal the key influencing mechanism of Ambidextrous Innovation driven by artificial intelligence, and make an empirical test, which makes a contribution to the literature of Ambidextrous Innovation of artificial intelligence and organization; (3) Based on the resource-based theory, this research analyzes the influence of different AI capabilities on organizational Ambidextrous Innovation and the priority of resources, which contributes to the practice of Ambidextrous Innovation in enterprises.

II. Literature review

A. *Artificial intelligence capabilities*

Since its emergence in the mid-1950s, artificial intelligence has been characterized in numerous ways, yet a universally agreed-upon definition remains elusive. Building upon previous research definitions and extending the perspectives of Mikalef and Gupta [6], we propose, grounded in the resource-based theory of enterprises, that artificial intelligence encompasses technologies and competencies pertinent to enterprises. We define artificial intelligence capabilities as the capacity to methodically discern, interpret, deduce, and adapt from data to accomplish predetermined organizational and societal objectives. The artificial intelligence capabilities have fundamentally changed the way of enterprise operation and development, and will play a powerful catalytic role in the process of enterprise innovation. However, there is still a lack of research on how artificial intelligence capabilities affect organizational innovation and through what mechanism.

Based on the foundation of resource-based theory, the empirical work of adopting resource-based theory in the field of information systems, and the latest research summarizing the challenges related to the adoption and value generation of artificial intelligence, we adopt eight kinds of resources proposed by Mikalef and Gupta, and think that they together constitute the artificial intelligence capabilities [6]. These resources may either be directly possessed by core enterprises or acquired through service agreements. We categorize the identified resources into three main groups: tangible resources, human resources, and intangible resources. Research shows that organizations with these resources will implement artificial intelligence more successfully, artificial intelligence will also create greater value, and artificial intelligence-related resources can improve organizational performance and creativity.

This study will analyze the influence mechanism of AI capabilities on organizational Ambidextrous Innovation in terms of tangible resources that are easy to measure. While these three capabilities are crucial in both information technology systems and the application of artificial intelligence, their respective contexts and emphases differ. Data capability refers to an organization's ability to collect, store, manage, and analyze data. Technical capability encompasses the knowledge and skills required to develop and maintain systems. Fundamental resource capability involves providing the necessary infrastructure, hardware, personnel, and financial resources for a project. Although the boundaries between information technology and artificial intelligence can sometimes blur due to their interconnections, in essence, data capability, technical capability, and fundamental resource capability in AI are extensions and expansions built upon the foundation of information technology systems. While they share connections, they also exhibit distinctions. Our measurement and assessment of these three capabilities will place a greater emphasis on their application in the context of AI.

B. The impact of artificial intelligence capabilities on enterprise performance

In recent years, there are more and more researches on how artificial intelligence affects organizations. The latest research thinks that artificial intelligence can help to generate high commercial value, such as predicting macro factors of entrepreneurial opportunities [11], promoting manufacturing development [12], and promoting sustainable manufacturing and circular economy [13]. In addition, according to the practitioner's point of view, using artificial intelligence can reach more customers through targeted procedures in marketing, which not only improves the efficiency of operation, but also opens the way for new operation methods [14]. Artificial intelligence capabilities are very important to an organization, which indirectly affect its performance and improves its competitive advantage [15]. Moreover, artificial intelligence capabilities have a far-reaching impact on Ambidextrous Innovation. It provides great opportunities for cross-domain innovation and promotes the integration and cross-innovation between different fields.

Although artificial intelligence technology has made remarkable progress in the past few years, many organizations have not successfully transformed technology into commercial value [15]. Many enterprises still face many challenges in realizing value from artificial intelligence investment, such as data quality and availability, technical complexity and lack of knowledge, cultural and organizational changes, privacy and ethical issues, etc. Accelerating the establishment of artificial intelligence capabilities can significantly improve these problems. Although the gap in the organization's artificial intelligence capabilities will lead to the performance gap, this gap is not always obvious [16]. At the same time, it is often difficult for organizations to honestly evaluate their artificial intelligence capabilities [17].

To sum up, organizations are facing important challenges and opportunities in the establishment and utilization of artificial intelligence capabilities. By fully developing artificial intelligence capabilities, organizations can better face changes and challenges, thus achieving higher performance, creating greater value, and maintaining a competitive advantage in the ever-changing business environment.

III. Research Model and Hypotheses

Based on the above discussion and theoretical basis, this study holds that artificial intelligence capability is an important antecedent for organizations to achieve Ambidextrous Innovation performance, and includes three dimensions (organizational capability): data capability, technical capability and basic resource capability. By enhancing the intermediary role of organizational learning and agility (organizational response) and the moderate role of digital strategy (boundary conditions), the Ambidextrous Innovation (organizational behavior) of organizations is finally realized. Figure 1 shows the research model and related assumptions.

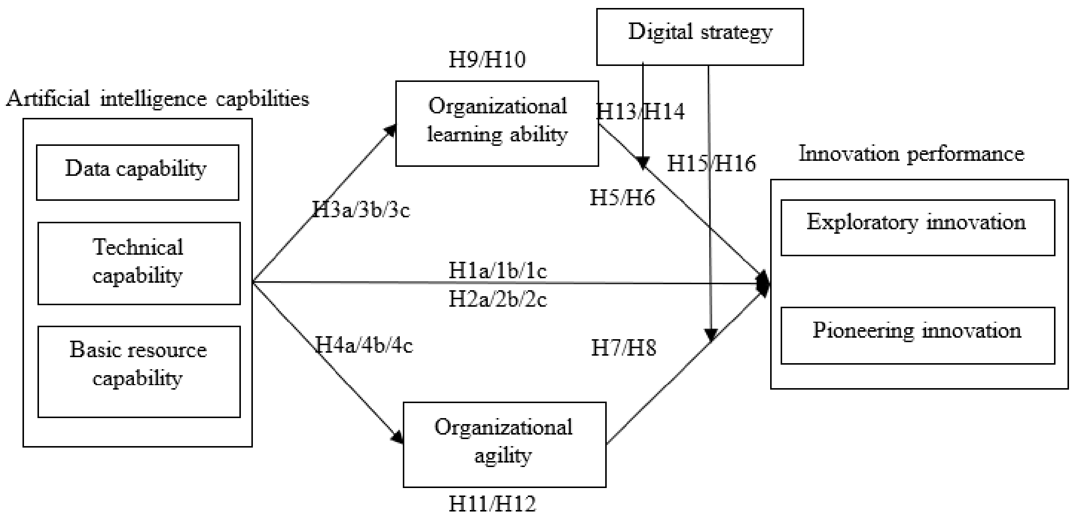

Figure 1 Research model

A. The impact of artificial intelligence capabilities on organizational Ambidextrous Innovation

Prior research has underscored the significance of artificial intelligence in fostering innovation and has also conducted an exploratory inquiry into the impact of artificial intelligence on innovation. Artificial intelligence is expected to become a new engine to promote company growth and improve innovation efficiency. With the vigorous development of new technologies, enterprises rely more and more on resources and internal capabilities to strengthen and accelerate internal innovation, and resources become more and more important [18]. By acquiring and utilizing resources, enterprises can significantly improve their Ambidextrous Innovation.

This study adopts the Ambidextrous Innovation dimensions proposed by Jansen-exploratory innovation and pioneering innovation [19]. Exploratory innovation refers to exploring unknown areas and finding new problems and solutions by developing new ideas, concepts and technologies. Artificial intelligence can provide a lot of data and computing power, help organizations to conduct data mining and analysis, discover new patterns and trends, thus promoting the implementation of exploratory innovation.

Pioneering innovation refers to opening up new business opportunities by applying existing technologies and resources to new markets and new fields. Artificial intelligence can help organizations better understand market demand and customer behavior, identify potential market opportunities through data analysis and prediction, help organizations open up new business models and service areas, and realize pioneering innovation. Hence,

H1: Artificial intelligence capabilities (a- data, b- technology, c- basic resources) have a significant positive impact on pioneering innovation.

H2: Artificial intelligence capabilities (a- data, b- technology, c- basic resources) have a significant positive impact on exploratory innovation.

B. The influence of artificial intelligence capabilities on organizational learning ability and agility

Artificial intelligence is usually associated with learning and reasoning, decision-making creation and other functions [20], while artificial intelligence capability reflects the strength of an organization's ability to predict and make intelligent decisions based on automatic machine learning, artificial neural network, robot process automation and text mining [21]. The establishment of artificial intelligence capabilities enables organizations to apply advanced analysis and logic-based technologies, including machine learning to explain events, support and automate decision-making and take actions, which enables enterprises to better analyze big data and make predictions, greatly improving the ability of enterprise knowledge acquisition, transformation and application [22]. Hence,

H3: Artificial intelligence capabilities (a- data, b- technology, c- basic resources) have a significant positive impact on organizational learning ability.

With the intensification of global competition, the rapid progress of technology and the shortening of product life cycle, enterprises are facing unprecedented pressure. They must make rapid moderates and introduce new innovative products and services to cope with customer needs and market changes, so as to survive in the competition and remain competitive. Innovation based on information technology is the key factor of organizational agility [23-25]. Lu and Ramamurthy found a positive correlation between IT capability and organizational agility [23]. AI capabilities can improve the response speed of perceiving and quickly capturing operational opportunities, and quickly respond to dynamic changes in internal and external environments, so as to enhance organizational agility. Hence,

H4: Artificial intelligence capabilities (a- data, b- technology, c- basic resources) have a significant positive impact on organizational agility.

C. The intermediary role of organizational learning and organizational agility

Previous studies have shown that organizational learning ability is regarded by academics and practitioners as the key to improve enterprise innovation performance and meet new business challenges. If enterprises can acquire knowledge from the outside in time, turn the learned knowledge into the company's assets and apply it to their operations, then they can adjust their core competitiveness and find emerging technologies and markets faster than their competitors, thus promoting exploratory innovation. Dynamic learning of enterprises can track potential customers in real time and improve customer experience and interaction with customers. Organizational learning ability not only enables enterprises to quickly perceive changing customer needs [26], but also can easily and quickly adjust their strategies to adapt to these changes, continuously improve products and services through learning and reflection, and promote the development of pioneering innovation. Hence,

H5: Organizational learning ability has a significant positive impact on pioneering innovation.

H6: Organizational learning ability has a significant positive impact on exploratory innovation.

In today's super competitive environment, agility is becoming one of the key organizational assets for innovation and competitive advantage [27-29]. If enterprises have organizational agility, they can quickly seize opportunities and take the lead in taking actions to innovate, and maintain speed and enthusiasm in operational actions [24]. According to previous research, it is proved that agile enterprises can easily enhance their operational advantages [30], quickly respond to market uncertainties, meet customer needs and create new opportunities. In this rapidly changing world, customers' preferences and tastes change rapidly, which brings great difficulties to enterprises. Changes in customer preferences and tastes will lead to the rapid obsolescence of products and services, which requires changing operational processes and rapidly introducing innovative products and services to satisfy customers [31]. Therefore, organizational agility can promote the implementation and promotion of pioneering innovation. Organizational agility not only enables enterprises to quickly perceive changing market and customer needs [32], but also can easily and quickly adjust their strategies and resource allocation, and discover new opportunities and trends in time, which greatly promotes organizational exploratory innovation. Hence,

H7: Organizational agility has a significant positive impact on pioneering innovation.

H8: Organizational agility has a significant positive impact on exploratory innovation.

Organizational learning ability (OLA) is an important variable in enterprise innovation. It is an act of learning knowledge to continuously optimize and innovate, and then generate value for organizations to profit from the digital artificial intelligence capabilities [33]. Organizational innovation is a dynamic process, which develops with the passage of time and the acquisition of knowledge and the improvement of efficiency. For exploratory innovation, organizational learning ability helps organizations to acquire and integrate knowledge and experience from different fields, cultivate the sensitivity of organizational members to new problems and opportunities, stimulate the awareness of innovation, discover and pursue new fields and possibilities, and create new ideas and solutions. For pioneering innovation, organizational learning ability helps organizations acquire and integrate knowledge about market demand and industry trends, identify and evaluate market opportunities, improve products and services, and open up new markets and fields. It can be seen that organizational learning ability plays an intermediary role in promoting Ambidextrous Innovation through knowledge acquisition and integration, insight and identification of opportunities, talent cultivation and capacity building, and promotion of cooperation and sharing. Hence,

H9: Artificial intelligence capabilities influence pioneering innovation through the intermediary effect of learning ability.

H10: Artificial intelligence capabilities influence exploratory innovation through the intermediary effect of learning ability.

Artificial intelligence capabilities can achieve agility by accelerating decision-making, promoting communication and quickly responding to changing conditions. Agility, on the other hand, emphasizes strategic direction, decision-making and judgment under uncertain conditions, and carries out reform and innovation for enterprises to cope with uncertain conditions. For pioneering innovation, organizational agility can help organizations quickly adjust the process of resource allocation and decision-making, so that organizations can better cope with the changes in external environment and the uncertainty of market demand, and carry out innovative practices flexibly to seize market opportunities and quickly open up new fields. For exploratory innovation, organizational agility can help organizations flexibly adjust their R&D direction and resource allocation, and promote organizations to learn and adjust quickly, so as to actively explore new technologies and solutions and adapt to the constant changes in technology and market. Accordingly, this study holds that organizational agility plays an intermediary role between artificial intelligence ability and Ambidextrous Innovation of enterprises. Hence,

H11: Artificial intelligence capabilities influence pioneering innovation through the mediating effect of organizational agility.

H12: Artificial intelligence capabilities influence exploratory innovation through the mediating effect of organizational agility.

D. The moderate role of digital strategy

Digital transformation is a corporate initiative aimed at proactively addressing changes in the business environment brought about by new digital technologies, significantly enhancing a company's competitive advantage, or pursuing new growth through innovative means [34]. Enterprises seek to achieve market differentiation and business competitiveness through digital strategies. These strategies provide support and enhance organizational learning capabilities and agility, which, in turn, impact innovation. The innovation within a company evolves alongside iterative upgrades of organizational capabilities and resource reallocation. Digital strategies facilitate rapid identification of changes and opportunities by providing real-time data and analytics, along with agile decision support tools, allowing organizations to swiftly adjust their strategies and resource allocation. Therefore, the formulation and implementation of a clear and strategic digital approach are crucial for the success of innovation in traditional enterprises.

In a highly digitized strategic environment, organizations can rapidly acquire and integrate knowledge and experience from different resources, utilizing technologies like big data analytics and machine learning. This enables them to unearth new technology trends and market demands, fostering continuous exploratory innovation. A highly digitized strategic environment offers better innovation infrastructure and support, enhancing the effectiveness of organizational learning capabilities and agility in driving exploratory innovation. Conversely, in a minimally digitized strategic environment, organizations may face constraints related to information acquisition, knowledge integration, and resource allocation, hindering their ability to effectively contribute to exploratory innovation.

In the realm of breakthrough innovation, a highly digitized strategic environment allows organizations to quickly access and analyze market information, identify shifts in market and customer needs, and promote internal reform and innovation through digital tools and data analytics. A highly digitized strategic environment provides more resources and support, reducing the costs and risks associated with breakthrough innovation. This encourages organizations to more effectively leverage their learning capabilities and agility to drive breakthrough innovation. In contrast, in a minimally digitized strategic environment, organizations may struggle with information acquisition and analysis, compounded by limited resources, making it difficult to respond promptly to the advancement of breakthrough innovation. Hence,

H13: Digital strategy positively regulates the influence of organizational learning ability on pioneering innovation.

H14: Digital strategy positively regulates the influence of organizational learning ability on exploratory innovation.

H15: Digital strategy positively regulates the influence of organizational agility on pioneering innovation.

H16: Digital strategy positively regulates the influence of organizational agility on exploratory innovation.

IV. RESEARCH DESIGN

A. Data collection

The management of enterprises with practical experience in artificial intelligence is the main investigator of this study, they have a comprehensive understanding of the operation of enterprises, and are familiar with the establishment of artificial intelligence capabilities. A total of 346 questionnaires were collected, and 253 valid questionnaires were used after excluding incomplete and randomly answered questionnaires, with an effective response rate of 73%.

Table 1 shows the demographic characteristics of the sample. The respondents aged 25-45 account for the majority, accounting for 90.51%. Male participants accounted for 61.26% and female participants accounted for 38.74%. 78.26% and 9.49% of the participants have bachelor's degrees and master's degrees respectively. The most representative sectors are computer/software sector (20.95%) and manufacturing industry (42.69%).

B. Measurement model

On the basis of the existing scale, this study improved it through group discussion, and used the 5-level Likert scale to measure it. We use the scale established by Mikalef and Gupta to measure the artificial intelligence capabilities [6], which is divided into three dimensions: AI data capability, AI technical capability and AI basic resource capability. We adopt the scale established by Li [35] for organizational learning ability and the scale established by Lu & Ramamurthy [24] for organizational agility. We adopt Jansen's scale and divide it into two dimensions: exploratory innovation and pioneering innovation [19]. For digital strategy, we adopt the scale established by AlNuaimi [36]. On the original basis, we made slight moderates according to the current situation to better conform to the current situation.

C. Reliability and validity test and correlation analysis

In this research, we used SPSS 25.0 and AMOS 24.0 to analyze the data. As can be seen from Table 2, the Cronbach's α value of the main variables in this study is between 0.800 and 0.897, which exceeds the minimum acceptable level of 0.6. The combined reliability (CR) of each variable is greater than 0.8, and the internal consistency is high. In terms of validity, confirmatory factor analysis shows that the measured model has a good fitting degree (CMIN/DF=1.825, RMESA=0.058, IFI=0.911, CFI=0.910, TLI=0.908), and the AVE of each variable is greater than 0.5, indicating that there is a good discrimination between variables. Table 3 shows the correlation coefficient of each variable, and the diagonal shows the square root of AVE of each variable.

Table 1 Distribution characteristics of samples

characteristic		sample	percentage	characteristic		sample	percentage
Gender	Man	155	61.26%	Position	Top management Staff	31	12.25%
	Woman	98	38.74%		Senior management	106	41.90%
Age	18-24	13	5.14%		Middle level managers	104	41.11%
	25-35	183	72.33%		Other	12	4.74%
	36-45	46	18.18%	Working life	Less than 1 year	1	0.40%
	46-55	11	4.35%		1-3 years	37	14.62%
Academic degree	High school and below	5	1.98%		4-6 years	86	33.99%
	Universities and colleges	26	10.28%		More than 6 years	129	50.99%
	Undergraduate college	198	78.26%	Corporate nature	Private enterprise	154	60.87%
	Graduate students and above	24	9.49%		State-owned and state-controlled enterprises	44	17.39%
Industry	Computer science and technology	53	20.95%		Full foreign-owned enterprises	38	15.02%
	Banking and finance	14	5.53%		Joint-stock companies	17	6.72%
	Manufacturing industry	108	42.69%	Company size	Miniature (1-9 people)	5	1.98%
	ICT and Telecommunications	37	14.62%		Small (10-49 people)	40	15.81%
	counseling	10	3.95%		Medium (50-249 people)	137	54.15%
	Consumer service	16	6.32%		Large (250 people and above)	71	28.06%
	Medium	4	1.58%	Artificial intelligence experience	Less than a year	10	3.95%
	Hygiene	3	1.19%		1-2 years	65	25.69%
	Other	8	3.16%		3-4 years	91	35.97%
					More than 4 years	87	34.39%

Table 2 Test results of reliability and validity of the scale

variable	Item	Factor load
AI data capability α=0.892 CR=0.892 AVE=0.58	We can access very large, unstructured or rapidly changing data for analysis.	0.782
	Data from multiple internal sources are integrated into a data warehouse for easy access.	0.791
	We combine external data with internal data to conduct high-value analysis of our business environment.	0.763
	Our internal data can be shared across departments.	0.718
	We can effectively prepare and clean up artificial intelligence data and evaluate the errors in the data.	0.748

	We can get data at the right level of granularity, thus generating meaningful insights.	0.766
AI technical capability α=0.894 CR=0.895 AVE=0.549	We have explored or adopted cloud-based services to process data and perform artificial intelligence and machine learning.	0.769
	We have the processing power (such as CPU and GPU) to support artificial intelligence applications.	0.754
	Network infrastructure that supports application efficiency and scale is invested in our organization.	0.724
	We have explored or adopted parallel computing methods to process artificial intelligence data.	0.721
	Advanced cloud services are invested by our organization to realize complex artificial intelligence functions (for example, Microsoft cognitive services, Google cloud vision) on simple API calls.	0.697
	We invested in a scalable data storage infrastructure.	0.755
	We explored the artificial intelligence infrastructure to ensure the end-to-end protection of data with the most advanced technology.	0.762
AI basic resource capability α=0.860, CR=0.861 AVE=0.673	The artificial intelligence initiative has received sufficient funds.	0.804
	We have enough team members to complete the artificial intelligence project.	0.820
	Artificial intelligence projects have enough time to complete.	0.837
Organizational learning ability α=0.846 CR=0.788 AVE=0.542	The latest information and knowledge about market trends and technological development will be quickly grasped by us.	0.832
	We have the ability to obtain the information and knowledge of advanced technologies/products/services in the industry.	0.704
	Information on changes in customer and market demand will be grasped by us in a timely manner.	0.709
	In order to make better use of it, we can classify and integrate new knowledge.	0.659
	Employees in our company have often exchanged and discussed skills, experience and information related to their work.	0.687
	We have the ability to integrate internal and external knowledge and turn it into knowledge that is easy for employees to understand.	0.787
	We have the ability to effectively and flexibly use existing or newly acquired knowledge to cope with the turbulent environment.	0.771
	New technologies can be mastered by us in a short time to introduce products or carry out process innovation.	0.697
	We have the ability to develop new products or services by using new technologies and new knowledge.	0.775
Organizational agility α=0.861 CR=0.841 AVE=0.642	We meet the needs of customers for quick response and the special requirements put forward by customers; Our customers are full of confidence in our ability.	0.793
	Facing the fluctuation of market demand, we can rapidly adjust our production and service level.	0.795
	Whenever the supply of our suppliers is interrupted, we can quickly make necessary replacement arrangements and internal moderates.	0.789
	We will quickly make appropriate decisions for changes in market or customer needs.	0.818
	In order to better serve our market, we have been looking for countermeasures to reshape/rebuild our organization.	0.816
	Market-related changes and obvious confusion are regarded as a good opportunity for us to make quick profits.	0.784
Exploratory innovation α=0.882 CR=0.883 AVE=0.518	Demand beyond existing products and services will also be accepted by us.	0.728
	Novel products and fresh services were invented by us.	0.726
	Novel products and fresh services are applied by us in the local market.	0.778
	Novel products and fresh services will be commercialized by our organization.	0.672
	We often take advantage of new opportunities in new markets.	0.734
	New distribution channels are often explored and adopted by us.	0.693
	We regularly explore potential markets and find new potential customers.	0.703
Pioneering innovation α=0.897 CR=0.899 AVE=0.562	We often improve the provision of existing products and services.	0.752
	For existing products and services, we will make small adjustments regularly.	0.781
	We will improve the existing products and services and launch them in the local market.	0.82
	We have improved the supply efficiency of products and services.	0.766
	We have increased economies of scale in the existing market.	0.673

	The service has been extended by our organization to existing customers.	0.793
	Reducing the cost of internal processes is an important goal.	0.647
Digital strategic orientation α=0.800 CR=0.804 AVE=0.506	In order to achieve strategic unity with the government and partners, we will integrate digital services and adjust business strategies.	0.745
	We have a common view on the role of digital technology in business strategy.	0.708
	We plan together how digital technology will realize business strategy.	0.714
	Before making a strategic decision, we usually conduct appropriate negotiations.	0.678
The model fitting index: CMIN/DF=1.825, RMESA=0.058, IFI=0.911, CFI=0.910, TLI=0.908.		

Table 3 Correlation coefficient results

variable	1	2	3	4	5	6	7	8
AI data capability	0.761							
AI technical ability	0.308***	0.739						
AI basic resource capability	0.377***	0.322***	0.821					
Organizational learning ability	0.235***	0.263***	0.276***	0.618				
Organizational agility	0.291***	0.343***	0.319***	0.463***	0.715			
Digital strategy	0.344***	0.286***	0.18**	0.318***	0.343***	0.71		
Exploratory innovation	0.361***	0.395***	0.352***	0.579***	0.543***	0.323***	0.721	
Pioneering innovation	0.312***	0.289***	0.282***	0.471***	0.635***	0.372***	0.477***	0.749

Note: * * * means p <0.001, * * means p <0.01, * means p <0.05

V. ANALYSES AND RESULTS

A. Regression Analysis and Hypothesis Test

In this study, hierarchical regression analysis is used to test the main effects of AI data capability (AID), AI technical capability (AIT) and AI basic resource capability (AIBR) on exploratory innovation (EI) and pioneering innovation (PI) under the control of enterprise type (FT), enterprise industry (FI), enterprise scale (FS) and enterprise age of using artificial intelligence (AIY). And the mediating effect of organizational learning ability (OLA) and organizational agility (OA). At the same time, all models were diagnosed with multicollinearity, and the VIF of each variable was less than 2, far below the critical value of 10, which indicated that multicollinearity was not serious. The specific regression results are shown in Table 4.

Table 4 is the analysis of hierarchical regression results. The path coefficient of AID to PI is positive (β=0.207, p<0.001), assuming that H1a holds. The path coefficient of AIT to PI is positive (β=0.232, p<0.001), assuming H1b is established. The path coefficient of AIBR to PI is positive (β=0.186, p<0.05), assuming that H1c holds.

The path coefficient of AID to EI is positive (β=0.179, p<0.01), which proves that hypothesis H2a is valid. The path coefficient of AIT to EI is positive (β=0.207, p<0.01), which proves that hypothesis H2b is valid. The path coefficient of AIBR to EI is positive (β=0.148, p<0.05), assuming that H2c holds.

The path coefficient of AID to OLA is positive (β=0.138, p<0.05), assuming that H3a holds. The path coefficient of AIT to OLA is positive (β=0.179, p<0.01), assuming H3b is established. The path coefficient of AIBR to OLA is positive (β=0.147, p<0.05), assuming that H3c holds.

The path coefficient of AID to OA is positive (β=0.148, p<0.05), assuming that H4a holds. The path coefficient of AIT to OA is positive (β=0.237, p<0.001), assuming that H4b holds. The path coefficient of AIBR to OA is positive (β=0.187, p<0.01), assuming that H4c holds.

The path coefficient of OLA to PI is significantly positive (β=0.416, p<0.001), assuming that H5 holds. The path coefficient of OLA to EI is positive (β=0.225, p<0.01), assuming that H6 holds.

The path coefficient of OA to PI is significantly positive (β=0.350, p<0.001), assuming that H7 holds. The path coefficient of OA to EI is significantly positive (β=0.531, p<0.001), assuming that H8 holds.

Table 4 Results of Hierarchical Regression Analysis

variable	OLA	OA	EI		PI	
Control variable						
FT	-0.086	-0.002	0.057	0.057	0.011	0.011
FI	-0.041	-0.124	-0.031	-0.031	-0.108	-0.108
FS	0.034	-0.028	-0.02	-0.02	-0.079	-0.079
AIY	0.164*	0.006	0.017	0.017	0.046	0.046
independent variable						
AID	0.136*	0.148*	0.179**		0.207***	
AIT	0.179**	0.237***	0.207**		0.232***	
AIBR	0.147*	0.187**	0.148*		0.186*	
mediator variable						
OLA				0.225***		0.416***
OA				0.531***		0.350***
R^2	0.151	0.195	0.158	0.452	0.259	0.496
ΔR^2	0.111	0.179	0.153	0.447	0.239	0.423
F	6.060***	17.722***	14.461***	97.791***	25.870***	91.073***

B. *Mediation effect test*

Next, we test whether OLA and OA play an intermediary role between AIC and PI and EI. We construct four models, AIC-OLA-PI, AIC-OLA-EI, AIC-OA-PI and AIC-OA-EI, to test the intermediary role between OLA and OA. In order to analyze the mediating effect of the two learning methods more intuitively, this paper uses bootstrap method to verify the parallel mediating effect of organizational agility and knowledge sharing. The specific results are shown in Table 5.

Table 5 Test Results of Intermediation

path	Effect value	SE	Bia-corrected 95% CI		
			Lower	Upper	P
AIC-OLA-PI	0.182	0.087	0.088	0.364	***
AIC-OLA-EI	0.108	0.09	0.012	0.236	*
AIC-OA-PI	0.113	0.063	0.017	0.224	*
AIC-OA-EI	0.233	0.105	0.106	0.415	***

Table 5 is an analysis of the mediating effect of OLA and OA in the relationship between AIC-PI and AIC-EI. The indirect effect of AIC → OLA → PI path is 0.182, and its confidence interval is [0.088, 0.362], which does not include 0, indicating the existence of this indirect effect and proving the hypothesis H9. The indirect effect of AIC → OLA → EI path is 0.108, its confidence interval is [0.012, 0.236], excluding 0, and the significance is p<0.05, which shows that this indirect effect exists and proves that hypothesis H10 is established. The indirect effect of the path of AIC → OA → PI is 0.083, and its confidence interval is [0.017, 0.224], which does not include 0, indicating the existence of this indirect effect and proving the hypothesis H11. The indirect effect of the path of AIC → OA → EI is 0.233, and its confidence interval is [0.106, 0.415], which does not include 0, indicating the existence of this indirect effect and proving the hypothesis H12.

C. Moderation Effect Test

This paper further examines the moderating effect of digital strategy (DS) on organizational learning ability (OLA), organizational agility (OA), exploratory innovation (EI) and pioneering innovation (PI) under the control of enterprise type (FT), enterprise industry (FI), enterprise scale (FS) and enterprise artificial intelligence age (AIY). Table 6 shows the moderating effect of digital strategy.

Table 6 Analysis of Moderation Effect

variable	PI		EI	
Control variable				
FT	0.058	0.047	0.058	0.04
FI	0.038	0.04	0.039	0.034
FS	0.02	0.021	0.02	0.018
AIY	0.053	0.055	0.054	0.047
independent variable				
OLA	0.356***		0.356***	
OA		0.472***		0.56***
moderator				
DS	0.329***	0.238***	0.329***	0.245***
Interaction item				
OLA*DS	0.165***		0.165***	
OA*DS		0.15***		0.128***
R^2	0.404	0.341	0.307	0.466
ΔR^2	0.387	0.333	0.298	0.441
F	23.186***	17.62***	15.108***	27.486***

From the results in Table 6, we can see that the regression coefficient of the interaction between OLA*DS to PI is positive (β=0.180, p<0.001). It shows that the greater the digital strategic orientation value, the higher the pioneering innovation value. The smaller the numerical value of digital strategy, the lower the degree of digital strategy. Therefore, digital strategy plays a positive moderate role between organizational learning ability and pioneering innovation, assuming H13 is established. Similarly, the regression coefficient of the interaction between OLA*DS to EI is significantly positive (β=0.165, p<0.001), which shows that digital strategy plays a positive moderate role between organizational learning ability and exploratory innovation, assuming H14 holds. The regression coefficient of the interaction between OA*DS to PI is positive (β=0.150, p<0.001), and digital strategy plays a positive moderate role between organizational agility and pioneering innovation, assuming that H15 holds. The regression coefficient of the interaction between OA*DS to EI is significantly positive (β=0.128, p<0.001), and digital strategy plays a positive moderate role between organizational agility and exploratory innovation, assuming that H16 holds.

According to the results of the moderate effect in Table 6, Table 7 further illustrates the moderate effect values of organizational learning ability and organizational agility at different levels of digital strategy, and draws the moderate effect diagram (Figure 2- Figure 5). Under the strategy of low, medium and high digitalization, the organizational learning ability has a vital effect on the pioneering simple slope, with coefficients of 0.382, 0.536 and 0.690 respectively. Once again, it is proved that the hypothesis H13 holds and it is positively regulated. Under the low, medium and high digital strategy, the simple slope of organizational learning ability to exploratory innovation is significant, with coefficients of 0.231, 0.360 and 0.490 respectively. Once again, it is proved that the hypothesis H14 holds and it is positively regulated. Under the low, medium and high digital strategies, organizational agility has a significant effect on the pioneering simple slope, with coefficients of 0.314, 0.408 and 0.502 respectively. Once again, it is proved that assumption H15 holds and it is positive regulation. Under the low, medium and high digital strategies, the simple slope of organizational agility to exploratory innovation is significant, with coefficients of 0.373, 0.447 and 0.521 respectively. Once again, it is proved that hypothesis H16 was supported.

Table 7 Moderating Effects on Different Levels of Digital Strategy

	Digital strategy	Effect value	Boot standard error	Boot CI lower limit	Boot CI upper limit
OLA-PI	M-1SD	0.382	0.086	0.213	0.551
	M	0.536	0.06	0.418	0.654
	M+1SD	0.69	0.068	0.556	0.824
OA-PI	M-1SD	0.314	0.066	0.185	0.444
	M	0.408	0.049	0.313	0.504
	M+1SD	0.502	0.058	0.388	0.616
OLA-EI	M-1SD	0.231	0.084	0.064	0.397
	M	0.36	0.059	0.244	0.477
	M+1SD	0.49	0.067	0.358	0.622
OA-EI	M-1SD	0.373	0.056	0.264	0.483
	M	0.447	0.041	0.366	0.528
	M+1SD	0.521	0.049	0.424	0.617

Fig. 2 The moderating effect of digital strategy in the relationship between organizational learning ability and pioneering innovation

Fig. 3 The moderating effect of digital strategy in the relationship between organizational learning ability and exploratory innovation

Fig. 4 The moderating effect of digital strategy in the relationship between organizational agility and pioneering innovation

Fig. 5 The moderating effect of digital strategy in the relationship between organizational agility and exploratory innovation

VI. Discussion

A. *Findings of research results*

This study conceptualizes and tests the influence of data capability, technical capability and basic resource capability of artificial intelligence on Ambidextrous Innovation, as well as the intermediary role of organizational learning ability and agility, and the moderate role of digital strategy. Research shows that artificial intelligence capability is a vital predictor of ambidextrous innovation, organizational learning ability and agility, and its intensity is different. In addition, this study also found that organizational learning ability and organizational agility play an important mediating role in the influence of artificial intelligence capabilities on Ambidextrous Innovation, and found that digital strategy is the moderate factor affecting the influence of artificial intelligence capabilities on Ambidextrous Innovation. The main research results are discussed:

Initially, artificial intelligence capabilities assist enterprises in enhancing both pioneering and exploratory innovation, with a varying effect on Ambidextrous Innovation. The results show that pioneering innovation requires more data, technology and basic resources. The collection of data, the application of technology and the support of basic resources can help organizations understand and explain market demand, customer feedback and competition, thus guiding the direction and decision-making of innovation and transforming ideas into actual products or services. Exploratory innovation depends more on organizational learning adaptability, innovative culture and innovative thinking, as well as individual innovative consciousness and openness. Therefore, in exploratory innovation, the influence of data, technology and basic resource capacity is relatively small.

Secondly, the artificial intelligence capabilities will help organizations to better improve their organizational learning ability and organizational agility. Data, technology and basic resource capability will all have an impact on organizational learning ability, among which technology has a stronger impact. Among the influences on organizational agility, technical capability plays the most significant role, while data capability has relatively little influence. We make an in-depth analysis of the reasons, because the quality and availability of data are often unstable, and it is also affected by timeliness, and only after correct interpretation can it play a role. Technology can provide new solutions, improve products or processes, and improve efficiency, help enterprises to speed up decision-making, and directly promote organizational learning.

Furthermore, organizational learning ability and organizational agility will help enterprises to carry out pioneering innovation and exploratory innovation. Compared with organizational agility, organizational learning ability has a greater effect on pioneering innovation. Organizational learning ability can help organizations learn and improve from market feedback, promote internal cooperation and knowledge sharing, and improve organizational innovation ability. Although organizational agility can help organizations adapt to market changes quickly, for exploratory innovation, organizational agility has a greater impact. Organizational agility can help organizations quickly adapt to market changes and flexibly adjust strategies and resource allocation, thus encouraging the exploration of new opportunities and solutions. Although organizational learning ability can help organizations learn and improve from market feedback, it has relatively little impact on exploratory innovation that explores new fields and opportunities.

Moreover, organizational learning ability and organizational agility not only affect organizational innovation, but also play a crucial intermediary role in the relationship between AI capabilities and Ambidextrous Innovation. Organizational learning ability supports Ambidextrous Innovation by promoting the learning and application of artificial intelligence technology and the occurrence and implementation of innovation; Organizational agility, on the other hand, adapts to the changing environment through rapid decision-making and action ability, and promotes the development of artificial intelligence capabilities and Ambidextrous Innovation. Together, the two promote the relationship and effect between artificial intelligence capabilities and Ambidextrous Innovation.

Finally, digital strategy plays a positive role in regulating organizational learning ability, organizational agility and Ambidextrous Innovation. It can promote the development of organizational learning ability, provide learning platforms and tools, and promote the precipitation, sharing and dissemination of knowledge, as well as cross-departmental and cross-organizational collaboration. Digital strategy can also enhance organizational agility, make the cooperation within the organization more efficient, make the resource allocation more flexible, and provide support for Ambidextrous Innovation. Therefore, in the digital age, digital strategy has important strategic significance and implementation value.

B. Research implications

1) Theoretical implications

This research aims to explore how enterprises can develop AI capabilities to accelerate innovation and achieve performance under the background of digital transformation. Recently, with the appearance of ChatGpt, artificial intelligence has increasingly become a hot spot, and it has become the future that enterprises are scrambling to chase. However, the research on how artificial intelligence affects enterprise innovation is still in its infancy. From the perspective of tangible resources needed by enterprises to build artificial intelligence capabilities, this paper studies its direct impact on organizational learning ability, agility and ambidextrous innovation, and also studies the intermediary role of organizational learning ability and agility. The results obtained not only test the assumptions put forward before, but also provide empirical insights for enterprises that are preparing or have applied artificial intelligence to their daily operations to accelerate the development steps of the innovation process. We provide tangible resources that need to be given priority in building artificial intelligence capabilities, and take artificial intelligence as a means to integrate into the daily operation of enterprises and accelerate enterprise innovation.

First of all, we describe in depth how to establish the artificial intelligence capabilities and the practice of developing artificial intelligence. In fact, many scholars have classified the resources that enterprises need to build artificial intelligence capabilities. However, the management literature rarely expounds what these resources are and the order in which enterprises develop them, and rarely analyzes the heterogeneity of the influence of different resources on Ambidextrous Innovation of enterprises. The conceptualization of artificial intelligence capability in this study is helpful to understand the operational mode of enterprises under the background of modern digitalization, and pays attention to the application of artificial intelligence and its role in enterprise operation.

Secondly, we have contributed to the literature of artificial intelligence and organizational innovation by revealing the key influencing mechanism of artificial intelligence driving organizational Ambidextrous Innovation. In our model framework, we emphasize the two key mediating roles of organizational learning ability and organizational agility. The artificial intelligence capability affects organizational Ambidextrous Innovation by influencing organizational learning ability and agility. These two intermediary variables reveal the influence mechanism of artificial intelligence to improve organizational innovation. This discovery emphasizes the importance of dealing with artificial intelligence in a holistic way when deployed within an organization. This study responds to previous studies to better understand how artificial intelligence creates value. This research can contribute to understanding how organizations apply learning and agility to optimize the innovation process, ultimately achieving higher levels of innovation.

Thirdly, we prove that the digital strategy of enterprises will affect the effect boundary of artificial intelligence capabilities. Enterprises can further expand the influence of artificial intelligence by adjusting their digital strategy. In the previous research, the influence of digital strategy on the use effect of artificial intelligence has not been proved. This paper takes digital strategy as a regulating variable to regulate the role of organizational learning ability and organizational agility in ambidextrous innovation, which is of innovative significance.

Finally, in this respect, consistent with the research, artificial intelligence capability can promote innovation by organizing learning and improving agility. In addition, the organization's digital strategy can indirectly affect the role of AI capabilities in innovation performance. At the same time, it shows the intermediary factors that artificial intelligence capabilities affect organizational innovation performance.

2) Managerial implications

Artificial intelligence has been proved to be the engine to accelerate the digital transformation of organizations, and enterprises that can firmly grasp the ability of artificial intelligence will surely gain a place in the competitive environment. Every enterprise is doing its best to carry out digital transformation driven by artificial intelligence. However, most managers lack direction on how to accelerate the establishment of artificial intelligence capabilities. Generally speaking, establishing the development direction of AI is a necessary prerequisite for organizations to establish artificial intelligence capabilities.

From the perspective of tangible resources, this study reveals how managers can invest in the best resources, quickly build artificial intelligence capabilities, and how to use artificial intelligence to achieve innovation in daily operations. Managers need to pay attention to mechanisms related to learning ability and agility to accelerate innovation transformation. We inherit the viewpoint of resource-based theory, divide artificial intelligence into three categories, and divide tangible resources into three specific resources, and compare their effects on Ambidextrous Innovation of enterprises, which provides a specific direction for managers to establish artificial intelligence capabilities. When organizations are pioneering innovation, data and technology are the resources that they should give priority to. When carrying out exploratory innovation, tangible resources are not the key factors. Up to now, there have been many literatures on the importance of organizational resources to artificial intelligence, but most of them are studied from the perspective of holistic theory. Our empirical investigation focuses on tangible resources, examining the individual impact of specific resources, yielding more detailed and dependable results.

The results of theoretical research can provide guidance for managerial practices, allowing organizations to leverage these research findings to enhance their learning capabilities and agility. Our research outcomes offer effective recommendations for enterprises seeking to accelerate their innovation transformation through the use of artificial intelligence. This AI capability provides organizations with convenience in terms of agility, learning, and innovation, helping them better understand how to leverage AI to improve their innovation processes. This includes automating repetitive tasks through AI, freeing up employees' time, and using AI analytics tools to extract insights and discover new opportunities.

At the same time, we find that digital strategy will also affect the mechanism between artificial intelligence and innovation performance. Enterprises can adjust their digital strategic orientation and establish artificial intelligence capabilities to speed up the innovation process, thus improving their competitiveness.

C. Limitations and future research

Some limitations exist in this study, which provides opportunities for future research. First of all, the respondents come from enterprises in different regions or enterprises with backward artificial intelligence technology. Some enterprises choose to outsource artificial intelligence solutions, which means that the demand for developing artificial intelligence capabilities within enterprises is reduced, and enterprises in different geographical regions and different artificial intelligence deployment stages can be investigated in the future. Second, although we rely on the managers in the company, choosing a single interviewee may contain some bias in the results. Thirdly, the respondents of this paper come from different industries (mainly from manufacturing enterprises). In the future, the use of artificial intelligence will involve a wider range of regional industries, so we can choose a single specific industry to study the impact of artificial intelligence.

VII. Conclusion

This research reinforces the study of artificial intelligence capabilities, highlighting AI's impact and contribution to organizational innovation. It encourages interdisciplinary collaboration involving fields such as organizational studies, information technology, innovation management, and strategy. Artificial intelligence can promote organizations to learn new knowledge, and transform knowledge to be applied to daily operations, and make flexible moderates to market changes. Through this study, we can enrich the academic literature in this field. Generally speaking, this research is the latest exploration of organizational artificial intelligence capability and organizational innovation.

References

[1] Kamoonpuri, S. Z., & Sengar, A. (2023). Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail. Journal of Retailing and Consumer Services, 72, 103258.

[2] Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., & Kiron, D. (2019). Winning with AI. MIT Sloan management review.

[3] Brock, J. K. U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. California Management Review, 61(4), 110-134.

[4] Anton, E., Behne, A., & Teuteberg, F. (2020). The humans behind Artificial Intelligence–An operationalisation of AI competencies.

[5] Watson, H. J. (2017). Preparing for the cognitive generation of decision support. MIS Quarterly Executive, 16(3).

[6] Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434.

[7] Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., ... & Niehaves, B. (2022). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. Government Information Quarterly, 39(4), 101596.

[8] Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. Journal of Business Research, 134, 574-587.

[9] Rammer, C., Fernández, G. P., & Czarnitzki, D. (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. Research Policy, 51(7), 104555. https://doi.org/10.1016/j.respol.2022.104555.

[10] Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. Long range planning, 52(3), 326-349.

[11] Jabeur, S. B., Ballouk, H., Mefteh-Wali, S., & Omri, A. (2022). Forecasting the macrolevel determinants of entrepreneurial opportunities using artificial intelligence models. Technological Forecasting and Social Change, 175, 121353.

[12] Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2022). Adoption of AI-empowered industrial robots in auto component manufacturing companies. Production Planning & Control, 33(16), 1517-1533.

[13] Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. Technological Forecasting and Social Change, 163, 120420.

[14] Raghupathi, H., Choudhury, D., & Sfeir, C. J. (2022). Application of Artificial Intelligence in Market Knowledge and B2B Marketing Co-creation. In Machine Learning for Business Analytics (pp. 107-115). Productivity Press.

[15] Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of Information Management, 60, 102383.

[16] Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard business review, 96(1), 108-116.

[17] Desouza, K. C., Dawson, G. S., & Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. Business Horizons, 63(2), 205-213.

[18] Natalicchio, A., Ardito, L., Savino, T., & Albino, V. (2017). Managing knowledge assets for open innovation: a systematic literature review. Journal of Knowledge Management.

[19] Jansen, J. J., Van Den Bosch, F. A., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. Management science, 52(11), 1661-1674.

[20] Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms:: toward human-AI hybrids. Mis Quarterly, 43(1), iii-ix.

[21] Wang, Y., Xiong, M., & Olya, H. (2020, January). Toward an understanding of responsible artificial intelligence practices. In Proceedings of the 53rd hawaii international conference on system sciences (pp. 4962-4971). Hawaii International Conference on System Sciences (HICSS).

[22] Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.

[23] Gao, P., Zhang, J., Gong, Y., & Li, H. (2020). Effects of technical IT capabilities on organizational agility: The moderating role of IT business spanning capability. Industrial Management & Data Systems, 120(5), 941-961.

[24] Lu, Y., & K.(Ram) Ramamurthy. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. MIS quarterly, 931-954.

[25] Tallon, P. P., Queiroz, M., Coltman, T., & Sharma, R. (2019). Information technology and the search for organizational agility: A systematic review with future research possibilities. The Journal of Strategic Information Systems, 28(2), 218-237.
[26] Felipe, C. M., Leidner, D. E., Roldán, J. L., & Leal - Rodríguez, A. L. (2020). Impact of IS capabilities on firm performance: the roles of organizational agility and industry technology intensity. Decision Sciences, 51(3), 575-619.
[27] Ferraris, A., Degbey, W. Y., Singh, S. K., Bresciani, S., Castellano, S., Fiano, F., & Couturier, J. (2022). Microfoundations of strategic agility in emerging markets: empirical evidence of Italian MNEs in India. Journal of World Business, 57(2), 101272.
[28] Shams, R., Vrontis, D., Belyaeva, Z., Ferraris, A., & Czinkota, M. R. (2021). Strategic agility in international business: A conceptual framework for "agile" multinationals. Journal of International Management, 27(1), 100737.
[29] Bresciani, S., Ferraris, A., Santoro, G., & Kotabe, M. (2022). Opening up the black box on digitalization and agility: Key drivers and main outcomes. Technological Forecasting and Social Change, 178, 0-4.
[30] Lee, Y. M., & Yang, C. (2014). The relationships among network ties, organizational agility, and organizational performance: A study of the flat glass industry in Taiwan. Journal of Management & Organization, 20(2), 206-226.
[31] Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., ... & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. International journal of production economics, 226, 107599.
[32] Wang, Y., Pan, X., Chen, Y., & Gu, X. (2013). Do references in transferred patent documents signal learning opportunities for the receiving firms?. Scientometrics, 95, 731-752.
[33] Lyytinen, K., Sørensen, C., & Tilson, D. (2017). Generativity in digital infrastructures: A research note. In The Routledge companion to management information systems (pp. 253-275). Routledge.
[34] Kohnke, O. (2017). It's not just about technology: The people side of digitization. Shaping the digital enterprise: Trends and use cases in digital innovation and transformation, 69-91.
[35] Ning, L., & Li, J. (2018). Joint problem solving and organizational learning capacity in new product innovation. R&D Management, 48(5), 519-533.
[36] AlNuaimi, B. K., Singh, S. K., Ren, S., Budhwar, P., & Vorobyev, D. (2022). Mastering digital transformation: The nexus between leadership, agility, and digital strategy. Journal of Business Research, 145, 636-648.