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Big data analytics capability and social innovation: the mediating role of knowledge exploration and exploitation

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While many organizations have successfully leveraged big data analytics capabilities to improve their performance, our understanding is limited on whether and how big data analytics capabilities affect social innovation in organizations. Based on the organizational information processing theory and the organizational learning theory, this study aims to investigate how big data analytics capabilities support social innovation, and how knowledge ambidexterity mediates this relationship. A total of 354 high-tech companies in China, this study shows that big data analytics management, big data analytics technology, and big data analytics personnel capabilities all have positive effects on social innovation. In addition, both knowledge exploration and knowledge exploitation play a mediating role in this process. Furthermore, a polynomial regression and response surface analysis shows that social innovation increases when knowledge exploration and knowledge exploitation are highly consistent but declines when knowledge exploration and knowledge exploitation are inconsistent. This study not only provides new perspectives for understanding how big data analytics capabilities contribute to social innovation, complementing the existing literature on big data analytics capabilities and social innovation, but also provides important practical guidance on how organizations can develop big data analytics capabilities to improve social innovation and solve social problems in the digital age.

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Introduction

The increased concerns with sustainability in the global context have prompted organizations to pay more attention to social innovation in their business operations (Saka-Helmhout et al., 2022; Tjörnbo and McGowan, 2022). Social innovation as a socially-orinted innovation not only can help solve social problems more effectively, but also can provide organizations with opportunities to enhance their sustainable competitive advantage (Carayannis et al., 2020; Wang et al., 2023a). However, social innovation also brings resource challenges to organizations, such as challenges in capital, talent, and knowledge (Saka-Helmhout et al., 2022). An increasing number of organizations have thus turned to big data analytics capabilities to crack the resource pressure in order to deal with these challenges (Bonina et al., 2021).

Big data analytics capabilities have been found capable of facilitating organizations to address social issues and create sustainable values (Ashaari et al., 2021; Said et al., 2023; Wang and Hajli, 2017). However, most existing studies have explored the economic performance of big data analytics capabilities (Ferraris et al., 2019; Mikalef et al., 2019), somehow ignoring big data analytics capabilities' impact on social elements. The relationship between big data analytics capabilities and social innovation has not been adequately examined in the literature (Calic and Ghasemaghaei, 2021; Krishnamurthy and Desouza, 2014), even though it is well known that social innovation places the emphasis more on the creation of social values. Therefore, the relationship between big data analytics capabilities and social innovation in the organizational context remains unclear (Agarwal et al., 2018; Wang et al., 2023a). In response to this research gap, this study attempts to explore whether big data analytics capabilities affect social innovation from the information processing perspective.

In addition, it is equally important to understand how big data analytics capabilities affect social innovation in order to generate more practical implications in the organizational context. It is contended in this study that big data analytics capabilities may enhance social innovation through the process of knowledge management (Unceta et al., 2016). On the one hand, the organizational learning theory shows that organizations can increase their capabilities to compete by exploring and exploiting knowledge (Andriopoulos and Lewis, 2009; Crossan et al., 1999; Wang et al., 2023b), during which big data analytics capabilities can support employees to explore and exploit internal and external knowledge and thus facilitate the organizational learning process (Gupta and George, 2016). On the other hand, the urgent need for more social innovation in the organizational context also drives organizations to utilize their knowledge exploration and exploitation capabilities to generate the information needed for social innovation, which again can be facilitated by big data analytics capabilities (Unceta et al., 2016). Therefore, this study expects that knowledge exploration and exploitation mediate the relationship between big data analytics capabilities and social innovation. Furthermore, in most cases, knowledge exploration and knowledge exploitation are interrelated in a complex way that they can mutually reinforce or counteract the influence they have on organizational learning, depending on their configurations (Li et al., 2018). While past research has shown that either knowledge exploration or knowledge exploitation helps firms solve social problems (Unceta et al., 2016; Xu et al., 2022), little is known what is their joint effect on social innovation. To bridge such a gap, this study also attempts to explore the joint impact of knowledge exploration and exploitation on social innovation.

In order to answer the research questions discussed above, this study adopts the organizational information processing theory and the organizational learning theory to explore the relationships between big data analytics capabilities, knowledge exploration and exploitation, and social innovation. Based on the data from 354 Chinese high-tech firms, we aim to shed light on the impact of big data analytics capabilities on social innovation, and on the optimal configuration of knowledge exploration and knowledge exploitation in affecting social innovation. The findings of this study can expand the research on social innovation and bridge the research gaps in the relationship between big data analytics capabilities and social innovation, which helps gain a more comprehensive understanding of knowledge and technology requirements of social innovation. The results also provide useful and timely guidance for organizations to develop social innovation for better organizational performance. The remaining sections of this study are organized as follows: Section 2 provides a literature review; Section 3 develops hypotheses; Sections 4 and 5 provide empirical analysis and results, and the final section summarizes findings and implications of this study.

Literature review

Organizational information processing theory. The organizational information processing theory views information and its processing and management as a key factor to organizational performance. Organizational information processing theory holds that when organizations attempt to complete uncertain or ambiguous tasks, they need to simplify information requirements or enhance information processing capabilities through a series of organizational system designs to effectively utilize and manage information and to cope with market uncertainties for optimal firm performance (Galbraith, 1974; Gupta et al., 2019). As uncertainty increases, information processing capabilities must also increase to accommodate information requirements (Yu et al., 2021). Information processing capabilities with strong ability to collect, analyze, and integrate data can cope with changes in uncertain market environments and thus promote innovation (Yu et al., 2021; Xie et al., 2022).

Organizational information processing theory contends that organizations are able to enhance their information processing capabilities by investing in vertical information systems and by building horizontal relationships (Galbraith, 1974; Srinivasan and Swink, 2018). On the one hand, big data analytics capabilities, as an emerging big-data based information system, can provide organizations with an effective way to process acquired data, help accurately predict risks in the external environment (Liu et al., 2022), and efficiently deploy resources to meet vertical information processing requirements (Dubey et al., 2019), thereby improving the efficiency of organizations innovation decisions. On the other hand, as an essential means for organizations to build horizontal relationships, knowledge management capabilities are often closely related to organizational processes and interactions (Yu et al., 2021). Knowledge management capabilities can assist organizations in building relationships with external partners for information acquisition and integrating external information into internal knowledge systems, which also helps improve innovation decisions (Srinivasan and Swink, 2018). In addition, as social innovation mainly exists in highly ambiguous contexts, organizations need to use big data analytics capabilities and knowledge management capability to analyze and integrate relevant data both horizontally and vertically in order to promote effective decision-making for social innovation. As a result, organizational information processing theory provides a suitable theoretical framework for a better understanding of the relationship between big data analytics capabilities, knowledge exploration and knowledge exploitation, and social innovation, with big data analytics capabilities as a vertical information system and knowledge management capabilities as a horizontal information system.

Table 1 Research on big data analytics capabilities and innovation.

Independent variable	Typologies	Dependent variable	Theory	Author
Big data analytics capabilities (+)		Green innovation	Natural resource-based view	Al-Khatib (2022)
Big data analytics capabilities (+)		Supply chain innovation	Resource-base view	Bhatti et al. (2022)
Big data analytics capabilities (+)		Business model innovation	Dynamic capabilities view	Ciampi et al. (2021)
Big data analytics capabilities	Information technology capability(+); Personnel expertise capability(n.s.); Management capability(n.s.)	Eco-innovation	Resource-base view	Munodawafa and Johl (2019)
Big data analytics capabilities	Tangible resources(+); Human skills(+); Intangible resources(+)	Dual innovation	Resource-base view	Su et al. (2022)

Organizational learning theory. The central idea of organizational learning theory is that organizations develop new knowledge and insights from experiences, which has the potential to contribute to organizational behavior and improve future organizational performance (Argote and Hora, 2017). March (1991) classified organizational learning into exploration and exploitation, where exploration includes things captured by such as search, change, adventure, experimentation, play, flexibility, discovery, and innovation, and exploitation includes things such as improvement, selection, production, efficiency, choice, implementation, and execution. On this basis, Benitez et al. (2018) integrated the exploration and exploitation activities of organizational learning into the field of knowledge management, proposing knowledge exploration and knowledge exploitation. Through the process of organizational learning, organizations are able to facilitate the generation and development of competencies that enhance the organization's innovativeness and performance and its sustainable competitive advantage (Real et al., 2006; Ghasemaghaei and Calic, 2019). Therefore, drawing on the framework of organizational learning theory, this study considers knowledge exploration and knowledge exploitation as two types of learning activities for firms (Gupta et al., 2006), and explains how these two different types of learning activities can better contribute to the process of social innovation.

Big data analytics capabilities. Big data analytics capabilities refer to the abilities to leverage data management, technology, and personnel resources to obtain business insights and boost competitiveness to realize full strategic potentials, and big data analytics capabilities thus consist of big data analytics management capabilities, big data analytics technology capabilities, and big data analytics personnel capabilities (Akter et al., 2016; Kiron et al., 2013; Lavalle et al., 2011; Wang et al., 2023). Among them, big data analytics management capabilities include the planning, coordination, investment, and control of big data analytics (Kiron et al., 2013). Big data analytics technology capabilities are the information systems that collect, store, process, and analyze big data (Rialti et al., 2019), and big data analytics personnel capabilities include management, technical, business, and relationship capabilities (Wamba et al., 2017).

As shown in Table 1, existing studies often focus on the link between big data analytics capabilities and innovation, including green innovation, supply chain innovation, business model innovation, eco-innovation and dual innovation, mainly from a dynamic capability view and a resource-based view (Al-Khatib, 2022; Bhatti et al., 2022; Ciampi et al., 2021; Munodawafa and Johl, 2019; Su et al., 2022). However, only a few studies have explored big data analytics capabilities to help organizations solve social problems, and they are often based on qualitative case methods, Ashaari et al. (2021) state that big data analytics capabilities can drive data to improve decision-making in educational institutions and improve public education. Wang and Hajli (2017), and Mani et al. (2017) highlight that big data analytics capabilities can help healthcare organizations to analyse, predict and decide on patient data in a timely manner. However, few have employed empirical methods to examine the impact of big data analytics capabilities on social innovation in for-profit organizations that consider both economic and social effects. This study focuses on how big data analytics capabilities can be used to drive the development of social innovation.

Social innovation. Scholars have explored the definition of social innovation from different perspectives. On the one hand, social innovation is sometimes viewed as a social exchange process that integrates multiple promoting elements to address social needs and societal issues (Olszak, 2014; Neumeier, 2012). On the other hand, social innovation also focuses on the result of exploring products, services, and business models to meet social needs and increase economic profits (Wamba et al., 2017). Therefore, this study defines social innovation as a practical process by which organizations and stakeholders solve social problems that are difficult to solve by market or government in order to promote social justice and improve social living conditions, and ultimately create social and economic value for the whole society.

Social innovation is dynamic and complex, and it is influenced by different factors from organization, society, and technology, as shown in Table 2. Past research has discovered that social entrepreneurship, knowledge networks and corporate strategic orientation as organizational factors aid in the promotion of social innovation and the provision of long-term solutions to social problems (Ho and Yoon, 2022; Krlev et al., 2014; Mirvis et al., 2016). Social factors include institutional and environmental factors, where both institutional gaps and environmental unrest affect the growth of social innovation (Gasparin et al., 2021; Guerrero and Urbano, 2020; Onsongo, 2019). Further, IT can stimulate the realization of social innovations through enablement and generate social impacts in areas such as education, employment, environment and healthcare (Fursov and Linton, 2022; Suseno and Abbott, 2021). It has been noted that big data analytics(BDA) is beginning to be used as a new IT tool to support the development of social innovation (Batko, 2023). With the support of big data analytics capabilities, firms can quickly access and analyze huge amounts of data and derive important and useful information (Mikalef et al., 2018), providing support for companies to achieve social innovation. However, the challenge of how big data analytics capabilities can access and

Table 2 Research on the antecedents of social innovation.

Factor	Antecedent	Theory/Model	Methods	Author
Corporate factors	Social entrepreneurship	Innovation system theory	Case studies	Ho and Yoon (2022)
	Corporate strategic orientation	Knowledge-base view	Case studies	Mirvis et al. (2016)
	Knowledge networks	Social innovation framework model	Qualitative studies	Krlev et al. (2014)
Social factors	Institution	Institutional theory	Empirical studies	Guerrero and Urbano (2020)
			Case studies	Onsongo (2019)
	Environment	Social innovation theory	Case studies	Gasparin et al. (2021)
Technical factors	Information technology	Individual difference theory	Qualitative studies	Suseno and Abbott (2021)
	Enabling technology	PUSI model	Case studies	Fursov and Linton (2022)

analyze data for social innovation by allocating different resources is currently unresolved. Therefore, this paper will delve into the complex role of big data analytics capabilities in influencing social innovation through empirical research.

Knowledge ambidexterity. The organizational ambidexterity theory suggests that organizations that are able to simultaneously explore new knowledge while exploiting current knowledge can outperform their rivals while enhancing innovation, competitive advantage, and business sustainability (O'Reilly and Tushman, 2013). Based on the organizational ambidexterity theory and the organizational learning theory, scholars have explored the knowledge ambidexterity that encompasses knowledge exploration and knowledge exploitation (Benitez et al., 2018), where knowledge exploration emphasizes the discovery and pursuit of new or unresolved knowledge, skill, and processes, and is the stage of introducing new practices (Koryak et al., 2018); Knowledge exploitation is the practice of reusing, transforming, and applying existing or new knowledge in an organization to meet current needs and ensure survival (Crossan et al., 1999).

In order to achieve enterprise knowledge ambidexterity, scholars have focused on the influential role of IT infrastructure and IT capabilities (Benitez et al., 2018; Beck et al., 2014). Specifically, IT capabilities that rely on various digital technologies (e.g., big data capabilities, Internet capabilities) facilitate firms' access to new knowledge as well as the transformation of knowledge into usable and accessible forms for application in the organization (Ferraris et al., 2019; Javed et al., 2022). Moreover, knowledge management is an effective way for firms to realize social innovation (Maalaoui et al., 2020). Allal-Cherif et al. (2022) found social innovation depends on external knowledge exploration by multiple parties and firms' efforts to transform knowledge into technologies and products. Therefore, this paper will focus on the process of developing knowledge ambidexterity through big data analytics capabilities, so as to promote the development of corporate social innovation.

Hypothesis

Big data analytics capabilities and social innovation. Based on organizational information processing theory, big data analytics capabilities act as an organizational information processing capability that permits companies to improve data-driven decision-making and innovation ways, and is an critical driver for survival and growth of firm (Ferraris et al., 2019; Su et al., 2022). Studies have pointed out that big data analytics capabilities is a higher-order multidimensional construct that includes big data analytics management capabilities, big data analytics technology capabilities and big data analytics personnel capabilities (Akter et al., 2016). Based on organizational information processing theory, this study will explore the relationship between big data analytics capabilities and social innovation with big data analytics capabilities consisting of managerial capability, technological capability and personnel capability respectively.

Big data analytics management capabilities and social innovation. Big data analytics management capabilities refer to the business choices made by organizations and consists of four basic components: planning, investing, coordinating, and controlling (Akter et al., 2016). In highly uncertain environments, it becomes particularly important for businesses to embrace and improve big data analytics management capabilities to support social innovation. Big data analytics management capabilities begins with proper big data analytics planning process that identifies business opportunities and determines how big data-based models can enable innovation (Barton and Court, 2012). During the business planning process, companies can prioritize innovation to solve social problems. Big data analytics investments respond to cost effects and can help firms to develop smarter strategies based on investing in analyses of huge amounts of data (Akter et al., 2016). For example, big data analytics investments can be used to assist companies in adapting and developing strategies for sustainable growth. By reducing the cost of green product development and increasing profits, they can improve their competitive advantage while addressing social issues (Verhoef et al., 2016). In addition, the coordination and control of big data analytics facilitates cooperation between various business activities. By allocating resources and information between departments in a timely manner, it ensures efficient use of resources (Bag et al., 2020), enable continuous monitoring of innovation capabilities (Akter et al., 2016). Based on the big data analytics coordination and big data analytics control, enterprises can obtain information about social issues, collaborate with enterprise departments to allocate resources and information, and help enterprises effectively implement social innovation. Accordingly, we propose a first hypothesis:

H1a: *Big data analytics management capabilities are positively related to social innovation.*

Big data analytics technology capabilities and social innovation. Big data analytics technology capabilities are tool that can assist data technicians in developing, deploying, and supporting business extensions with connectivity, compatibility, and modularity (Akter et al., 2016). It can help organizations to be more aware of market trends, the business environment and social issues, and provide new directions and guidelines for social innovation. Technologies such as sensors and Radio Frequency Identification in big data analytics technology capabilities allow for product traceability recall, remanufacturing, recycling and reuse at the point of production (Okorie et al., 2018). These technologies not only increase the effectiveness and recycling of materials and the sustainability of businesses (Awan et al., 2021; Rashidin et al., 2021), but also minimize the social problem of waste in the production process and increase social innovation.

big data analytics technology capabilities also enables enterprises to collect and analyse data faster and more accurately, helping them to gain access to vital information related to consumer behavior and preferences (Su et al., 2022). Enabling social innovation by modeling various social scenarios. Sustainably changing energy production and consumption, improving its structure (Mikalef et al., 2020), eradicating poverty, and solving social problems (Alnuaimi et al., 2021). Thus, we propose the hypothesis:

H1b: *Big data analytics technology capabilities are positively related to social innovation.*

Big data analytics personnel capabilities and social innovation. Big data analytics personnel capabilities refer to the technical, technology management, business, and relational capabilities of data scientists to perform specific tasks in a big data environment, which are widely considered to play an important role in fostering innovation (Akter et al., 2016). Big data analysts can gather a variety of valuable information about the market and consumers by effectively integrating and analyzing big data (Müller et al., 2018; Deng et al., 2024). This information helps organizations to better understand market trends, guide business operations, and improve the quality of product and service development (Su et al., 2022). In terms of social value, big data analytics personnel capabilities has made a significant contribution to creating eco-friendly products and raising the social awareness of employees within the organization. Examples include increased compliance with legal requirements, protection from social and environmental issues, and corporate social innovation (Alnuaimi et al., 2021; Bag et al., 2020). Big data analytics personnel capabilities can also enhance data-driven insights, increase the level of understanding of business staff about current social issues and innovation generation. Improve material efficiency through effective decision-making and the use of technology to redesign products and services, and help organizations achieve a circular economy and promote social innovation (Awan et al., 2021). Thus, we propose the hypothesis:

H1c: *Big data analytics personnel capabilities are positively related to social innovation.*

The mediating role of knowledge ambidexterity. One of the main issues in the digital age is how to extract the necessary facts from large amounts of data and transform them into usable new knowledge. With the support of big data analytics capabilities, enterprises utilize data management, technical and person to obtain information (Akter et al., 2016), and enhance innovation capabilities through knowledge exploration and knowledge exploitation (Benitez et al., 2018).

First off, big data analytics management capabilities can support knowledge exploration at the strategic level of the organization by extracting the correct information from the data (Ferraris et al., 2019). Enterprises will spend a significant amount of money building knowledge management infrastructure (Sun et al., 2019). And then they can choose from a variety of methods of knowledge exploration through access, contextualization, experimentation, and application of big data insights. Secondly, big data analytics technology capabilities provide enterprises with a constant flow of external information to tap into the original ideas of different types of users in the innovation ecosystem (Zeng et al., 2010), and enrich the company's knowledge base. Finally, big data analytics personnel capabilities provide staff support for knowledge exploration. Previous research has overemphasized the influence of data software on knowledge ambidexterity and neglected the role of data analysts (Conboy et al., 2020). Organizations with excellent data analysts can achieve knowledge discovery by collecting, observing, analyzing, and condensing large amounts of fresh, unstructured information to rapidly generate new insights and valuable knowledge (He et al., 2015). Thus, we propose the following hypotheses:

H2a: *Big data analytics management capabilities are positively related to knowledge exploration.*

H2b: *Big data analytics technology capabilities are positively related to knowledge exploration.*

H2c: *Big data analytics personnel capabilities are positively related to knowledge exploration.*

In the dynamic perspective of knowledge, big data analytics management capabilities ensure knowledge application (Oeij et al., 2019). Big data analytics management capabilities's planning, co-ordination and control functions can be used to analyse disparate data to discover useful information and use it to improve knowledge exploitation. These functions can also be used to define big data analytics models used by the enterprise and build a cross-functional synchronization of the entire company analysis activities (Kiron et al., 2013). Big data analytics technology capabilities provide companies with various types of knowledge exploitation tools to improve coordination up and down the supply chain and to flexibly and quickly convert and exploit new organizational knowledge (Chen et al., 2017). In addition, IT infrastructure within the organization enhances internal coordination by facilitating cross-functional communication, allowing employees to share their business ideas and offer solutions to streamline the knowledge exploitation (Benitez et al., 2018). In big data analytics personnel capabilities, the business and interpersonal skills of big data analysts can support analysts to communicate and collaborate with others to understand the development needs of the market. It also generates new knowledge in the process of communication, improves the ability of the firm to use the knowledge inventory in a variety of situations, and facilitates knowledge exploitation in organizations (Nwankpa et al., 2022; Gebauer et al., 2020). Based on the above analyses, we propose the following hypotheses:

H3a: *Big data analytics management capabilities are positively related to knowledge exploitation.*

H3b: *Big data analytics technology capabilities are positively related to knowledge exploitation.*

H3c: *Big data analytics personnel capabilities are positively related to knowledge exploitation.*

Knowledge-based social services have been shown to help firms achieve innovation and improve innovation performance (Desmarchelier et al., 2020). Knowledge exploration can produce more cutting-edge analytical capabilities and knowledge resources, which can help organizations overcome difficulties in innovation (Xiao and Oh, 2021). Knowledge exploitation enables organizations to continuously improve their understanding of knowledge, identify and absorb corporate knowledge more effectively. It also enables the creation of new models of innovation and the creation of value through digital technologies to improve innovation outcomes (Benitez et al., 2018). When an organization must apply social innovation in a different culture, it must survey relevant information with its partners or users to build the knowledge resources needed for social innovation through dialog and communication (Herrera, 2015). Based on the above analysis, we propose the following hypotheses:

H4a: *Knowledge exploration is positively correlated with social innovation.*

H4b: *Knowledge exploitation is positively correlated with social innovation.*

In order to ensure that firms are able to gain a competitive advantage in a turbulent environment, organizations apply big data analytics capabilities to appropriate management frameworks to ensure that reliable business decisions are made (Akter et al., 2016). In practical, big data analytics capabilities require organizations to realize social innovation through the exploration and exploitation of knowledge in order to satisfy the unity of economic and social value.

As a dynamic capability, big data analytics management capabilities can help enhance the knowledge exploration ability of enterprises and enable them to obtain the required knowledge (Shamim et al., 2021). By constantly exploring knowledge, they can track unpredictable market trends and understand social problems and trends, so as to help companies to generate new solutions to address social issues and increase their social innovation. Secondly, big data analytics technology capabilities provide technical support for organizations to conduct knowledge exploration. By using big data analytics technology capabilities, organizations may acquire new knowledge from external markets and share knowledge with partners (Castillo et al., 2021). Thus, information about social innovation in the market is obtained, providing knowledge to help organizations realize social innovation. Finally, studies have shown that the big data analytics personnel capabilities can bring about changes in knowledge management and increase and expand personal knowledge (Pauleen, 2009). Big data analysts can thus work closely with other business department personnel to achieve knowledge and technology sharing in the communication process. Organizations can also obtain information about social issues in the collaboration and help solve them through social innovation. Based on the above analysis, we propose the following hypothesis:

H5a: *Knowledge exploration mediates the relationship between big data analytics management capabilities and social innovation.*

H5b: *Knowledge exploration mediates the relationship between big data analytics technology capabilities and social innovation.*

H5c: *Knowledge exploration mediates the relationship between big data analytics personnel capabilities and social innovation.*

Organizations equipped with big data analytics management capabilities are adept at feeding back the meaning of data-driven insights to internal departments (Mikalef et al., 2018). Internal knowledge development helps improve internal knowledge exploitation and foster technological and process advancements, which is beneficial for social innovation. Meanwhile, big data analytics technology capabilities can help organizations eliminate production failures and improve production techniques faster (Wang et al., 2018). The improvement in the production process through knowledge exploitation enables organizations to realize social innovation faster and contribute to the solution of social problems. In addition, when organization personnel master big data technology and business knowledge, they are more likely to transform them into actual innovations (Su et al., 2022). With big data analytics personnel capabilities, organizations can help achieve knowledge exploitation, reduce the failure in innovation transformation, and provide a knowledge base for organizations to carry out social innovation. Based on the above analysis, we propose the following hypothesis:

H6a: *Knowledge exploitation mediates the relationship between big data analytics management capabilities and social innovation.*

H6b: *Knowledge exploitation mediates the relationship between big data analytics technology capabilities and social innovation.*

H6c: *Knowledge exploitation mediates the relationship between big data analytics personnel capabilities and social innovation.*

Configurations of knowledge ambidexterity and social innovation. Considering that both knowledge exploitation and knowledge exploration are important contributors to social innovation, it is important to understand how the configuration of knowledge exploration and knowledge exploitation drives social innovation. There are four pairs of different configuration between knowledge exploration and exploitation, and among them, "high exploration-high exploitation" and "low exploration-low exploitation" being examples of consistent ability, and "high exploration-low exploitation" and "low exploration-high exploitation" being examples of inconsistent ability, as shown in Fig. 1.

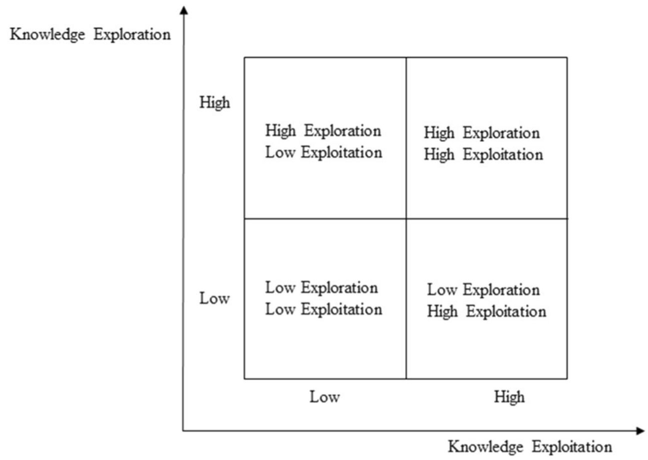

Fig. 1 Knowledge ambidexterity combination configuration.

In the "high exploration-high exploitation" scenario, high knowledge exploration can help firms to acquire new knowledge related to social innovation from both inside and outside the organization, expanding the firm's knowledge base and encouraging innovative thinking and idea sharing within the firm (Benitez et al., 2018). It can also provide access to different social information, perceive social problems, help organizations to see problems from different perspectives (Nicolopoulou et al., 2017), transform their potential knowledge into realized innovation (Cheng and Sheu, 2023), and thus can improve social innovation. High knowledge exploitation can encourage the use of a wide range of knowledge in the existing knowledge base to transform product development and design, increasing the competitive advantage of the firm (Sandberg and Aarikka-Stenroos, 2014). It also enables organizations to address social problems by creating service offerings that better meet the needs and expectations of local communities, which enhances social innovation (Ndou and Schiuma, 2020). In the "low exploration-low exploitation" scenario, it is difficult for firms to solve social problems because of weak exploration and exploitation capabilities, which make it difficult for organizations to acquire cutting-edge knowledge from external sources to update their knowledge base or create new knowledge. Therefore, we propose the following hypothesis:

H7a: *The level of social innovation is higher when both knowledge exploration and knowledge exploitation are high than when both are low.*

Not all companies can carry out highly balanced knowledge exploration and knowledge exploitation. Therefore, it is also important to consider the effects of unbalanced knowledge exploration and knowledge exploitation on social innovation. The unbalanced knowledge ambidexterity includes "high exploration-low exploitation" and "high exploitation-low exploration", both of them can be detrimental to the development of social innovation in organizations. When organizations are in the state of "high exploration-low exploitation", they get more fresh information and ideas from outside. However, excessive exploration may make it difficult for organizations to understand, absorb, and apply unfamiliar technologies inside the organizations (Fleming and Sorenson, 2001), resulting in increased search costs. Moreover, low knowledge exploitation cannot provide a foundation to transform acquired new knowledge, resulting in

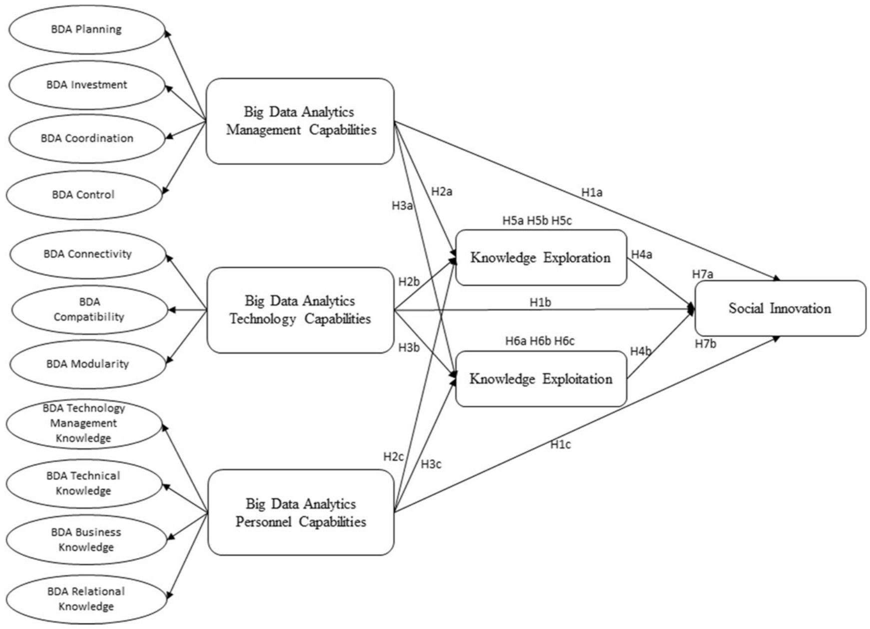

Fig. 2 Research model.

localization challenges in absorbing new knowledge (Ferreira et al., 2020),constraining social innovation in organizations. When organizations are in the state of "high exploitation-low exploration", they only obtain knowledge from their own existing knowledge bases. They are not able to obtain sufficient new information or ideas from external organizations, which are essential for their own social innovation. As a result, social innovation is also limited, resulting in the trap of familiarity (Li et al., 2018). Therefore, we propose the following hypothesis:

H7b: *When the imbalance between knowledge exploration and knowledge exploitation increases in either direction, social innovation will decline.*

Combining the above assumptions, we developed a conceptual model, which is shown in Fig. 2.

Research design

Respondent profiles. To test our hypotheses, we surveyed Chinese high-tech firms' CEOs and CIOs with information technology experience. The Digital China Development Report (2022) shows that China is the world's second largest data-producing country and has a high level of information technology adoption, which enables Chinese high-tech firms to use big data analytics capabilities to analyse large amount of data to create innovation opportunities. At the same time, Chinese high-tech companies often emphasize technology for good causes and thus actively address social issues through new technologies. In this study, we set the following sampling criteria: (1) participating firms must have been concerned about big data analytics capabilities and social issues in the last five years; (2) participating firms must have complete email contact information for their CEOs and CIOs so that they can be reached by emails.

Sample and data collecting processes. We used a random sampling technique to collect data. As "the statistical analysis report on the development of China's high-tech industry in 2020" states that Beijing, Zhejiang, Jiangsu, and Guangdong are home to a large number of high-tech companies in China, we randomly selected a sample of about 500 high-tech firms focusing on big data and social innovation through a local government's enterprise information database in Beijing, Zhejiang, Jiangsu, and Guangdong, and then distributed questionnaires to their CIO and CEO. The CIOs and CEOs were chosen to distribute the questionnaire because they are familiarize with corporate digital strategy and have the knowledge of social orientation in their organizations, and also have a clear understanding of the company's knowledge exploration and knowledge exploitation. We emailed a questionnaire to the CIOs of these companies covering basic information, big data analytics capabilities, and knowledge ambidexterity strategies in Time 1 (T1). In the end, 463 questionnaires were returned, of which 442 were valid. One year later (T2), we sent questionnaires by E-mail to the CEOs of these 442 companies that had returned valid questionnaires in T1 to collect data on social innovation. 402 questionnaires finally returned, of which 354 were valid. As shown in Table 3, the questionnaire asked the respondents about their gender, age, time of using big data analytics capabilities, age of the company, industry, and the size of the business.

Measurement of variables. All variable were measured using the scales designed based on well-known scales that have been widely used in previous research, and a two-way translation procedure was utilized to translate the scales. To ensure the validity of the scale, we contacted two experts in the fields of information systems and strategic management to review our questionnaire. According to experts' comments and suggestions, we further modified it to guarantee that all items were content valid. All items were validated on seven-point Likert scales ranging from 1 = "strongly disagree" to 7 = "strongly agree". Specific variables were measured as follows:

Big data analytics management capabilities, big data analytics technology capabilities and big data analytics personnel capabilities are the independent variables in this research. The scales were adapted from those used by Akter et al. (2016). The big data analytics management capabilities scale has 16 items, the big data analytics technology capabilities scale has 12 items, and the big data analytics personnel capabilities scale has 16 items.

Knowledge exploration is a mediating variable in this research. The scale was adapted from the one used by Cegarra-Navarro et al. (2011), with five question items.

Table 3 Sample demographics (*N* = 354).

Characteristics	Category	Frequency	Percentage
Gender	Male	200	56.5%
	Female	154	43.5%
Time to use Big data analytics capabilities	<1 year	7	2%
	1–3 years	48	13.6%
	3–5 years	97	27.4%
	5–7 years	109	30.8%
	7–9 years	70	19.8%
	>10 years	23	6.5%
Firm age	<5 years	44	12.4%
	5–10 years	99	28%
	10–15 years	99	28%
	15–20 years	89	25.1%
	>20 years	23	6.5%
Industry	Electronic communication	40	11.3%
	Software Service	66	18.6%
	Biomedical	43	12.1%
	Machinery manufacturing	78	22%
	Education	31	8.8%
	Internet	56	15.8%
	Other	40	11.3%
Size	<50 people	12	3.4%
	50–100 people	81	22.9%
	101–500 people	139	39.3%
	501–999 people	59	16.7%
	>1000 people	63	17.8%

Knowledge exploitation is another mediating variable in this research. The scale was adapted from the one used by Arias-Pérez et al. (2021), with five question items.

Social innovation is the dependent variable in this study. The scale was adapted from the scale used by Adomako and Tran (2022) and consists of five question items. Detailed measurements are shown in Table 4.

In addition, firm age, firm size and industry category are used as control variables as they may affect firms' innovative behavior. The details of the scale are shown in Table 5.

Analytical methods. A quantitative research method was used in this study. SPSS software, and AMOS software were used to analyze and process the data to maximize the validity of the questionnaire data testing (Jarjabka et al., 2024). In particular, SPSS analysis software was used to calculate the reliability and validity of the data, multiple regression, and response surface analysis. AMOS was used on construct structural methodological models to test hypotheses. The details of the scale are shown in Fig. 3.

Results

Reliability and validity. In this study, SPSS 25.0 was used to analyze the reliability of each variable. From the results in Table 6, the Cronbach's α values of variables are all greater than 0.7, above acceptable levels. The KMO of each variable is greater than 0.7, and the Bartlett's spherical test is significant, which was suitable for factor analysis. AVE values are all greater than 0.5 (Netemeyer et al., 2003), and CR values are all greater than 0.8 (Nunnally, 1994), indicating that the scale has good convergence validity and internal consistency. To examine discriminant validity, the correlation shared between the square AVE of the construct and any other construct is compared (Fornell and Larcker, 1981). As shown in Table 7, the measurement models have enough discrimination validity because the squared AVE is bigger than the shared correlation between the constructs. In general, all measures have sufficient reliability and validity.

Common method bias. We used procedural remedies and statistical tests to avoid common method bias. First, the dependent variable was collected in a different questionnaire from other variables and we made sure that everyone filled these questionnaires out anonymously. Second, we used Harman's one-way analysis of variance to test the common method bias (Harman, 1976), and the data showed that the unrotated first factor explained only 26.42% of the variance (less than 30%). In addition, we compared the fit of a one-factor model and the measurement model, with the one-factor model having the worse fit (χ^2(df) = 1547.677 (299)) than the measurement model (χ^2(df) = 434.335 (284)). Meanwhile, The RESEA of the measurement model was 0.039, χ^2/df = 1.529, and IFI, CFI, and TLI were all greater than 0.9. Therefore, the results indicate that there is no serious common method bias in this study.

Correlation analysis. The variables in this study were analyzed for correlation using SPSS25.0, and the findings are presented in Table 7. The correlations between the big data analytics management capabilities, big data analytics technology capabilities, big data analytics personnel capabilities, social innovation, knowledge exploration, and knowledge exploitation are positive. The variables have a positive association, which supports the hypothesis testing in the following section.

Hypothesis testing

Main effects test. We tested the H1-H4 hypotheses through structural equation modeling using AMOS (Bollen, 1989). We examined the VIF values before conducting the main effects test and the data showed that they were all less than 3, indicating that there was no significant multicollinearity problem.

Table 8 and Fig. 4 reports the results of the structural modeling analysis. The results show that big data analytics management capabilities ($\beta = 0.194$, $p < 0.01$), big data analytics technology capabilities ($\beta = 0.161$, $p < 0.01$) and big data analytics personnel capabilities ($\beta = 0.299$, $p < 0.001$) are all significantly and positively associated with social innovation, indicating that H1a, H1b and H1c are all supported. Big data analytics management capabilities ($\beta = 0.217$, $p < 0.01$), big data analytics technology capabilities ($\beta = 0.315$, $p < 0.001$), and big data analytics personnel capabilities ($\beta = 0.295$, $p < 0.001$) all positively affect knowledge exploration, and thus Hypotheses H2a, H2b and H2c are supported. Big data analytics management capabilities ($\beta = 0.194$, $p < 0.01$), big data analytics technology capabilities ($\beta = 0.265$, $p < 0.001$), and big data analytics personnel capabilities ($\beta = 0.557$, $p < 0.001$) also positively influence knowledge exploitation, thus supporting Hypotheses H3a, H3b, and H3c. In the study of knowledge exploration, knowledge exploitation and social innovation, the data suggests that knowledge exploration ($\beta = 0.134$, $p < 0.05$) and knowledge exploitation ($\beta = 0.252$, $p < 0.001$) positively affect social innovation, and Hypotheses H4a and H4b are supported.

Mediating effect test. Before testing the mediating effects, we assessed the effect of big data analytics capabilities on the relationship between knowledge exploration and knowledge exploitation, and the effect of knowledge exploration and knowledge exploitation on social innovation. The results in Table 8 show that big data analytics management capabilities, big data analytics technology capabilities, and big data analytics personnel capabilities significantly improve knowledge exploration and knowledge exploitation. Knowledge exploration and knowledge

Table 4 Measuring items.

Item	Description
BDAMC1	We continuously examine the innovative opportunities for the strategic use of big data analytics.
BDAMC2	We enforce adequate plans for the introduction and utilization of big data analytics.
BDAMC3	We perform big data analytics planning processes in systematic and formalized ways.
BDAMC4	We frequently adjust big data analytics plans to better adapt to changing conditions.
BDAMC5	When we make big data analytics investment decisions, we think about and estimate the effect they will have on the productivity of the employees' work.
BDAMC6	When we make big data analytics investment decisions, we consider and project about how much these options will help end-users make exploitation quicker exploitation decisions.
BDAMC7	When we make big data analytics investment decisions, we think about and estimate the cost of training that end-users will need.
BDAMC8	When we make big data analytics investment decisions, we consider and estimate the time managers will need to spend overseeing the change.
BDAMC9	In our organization, business analysts and line people meet frequently to discuss important issues both formally and informally.
BDAMC10	In our organization, business analysts and line people from various departments frequently attend cross-functional meetings.
BDAMC11	In our organization, business analysts and line people coordinate their efforts harmoniously.
BDAMC12	In our organization, information is widely shared between business analysts and line people so that those who make exploitation decisions or perform jobs have access to all available know-how.
BDAMC13	In our organization, the responsibility for big data analytics development is clear.
BDAMC14	We are confident that big data analytics project proposals are properly appraised.
BDAMC15	We constantly monitor the performance of the big data analytics function.
BDAMC16	Our analytics department is clear about its performance criteria.
BDATC1	Compared to rivals within our industry, our organization has the foremost available analytics systems.
BDATC2	All remote, branch, and mobile offices are connected to the central office for analytics.
BDATC3	Our organization utilizes open systems network mechanisms to boost analytics connectivity.
BDATC4	There are no identifiable communications bottlenecks within our organization when sharing analytics insights.
BDATC5	Software applications can be easily transported and used across multiple analytics platforms.
BDATC6	Our user interfaces provide transparent access to all platforms and applications.
BDATC7	Analytics-driven information is shared seamlessly across our organization, regardless of the location.
BDATC8	Our organization provides multiple analytics interfaces or entry points for external end-users.
BDATC9	Reusable software modules are widely used in new analytics model development.
BDATC10	End-users utilize object-oriented tools to create their own analytics applications.
BDATC11	Object-oriented technologies are utilized to minimize the development time for new analytics applications.
BDATC12	Applications can be adapted to meet a variety of needs during analytics tasks.
BDAPC 1	Our analytics personnel are very capable in terms of programming skills.
BDAPC 2	Our analytics personnel are very capable in terms of managing project life cycles.
BDAPC 3	Our analytics personnel are very capable in the areas of data and network management and maintenance.
BDAPC 4	Our analytics personnel create very capable decision support systems driven by analytics.
BDAPC 5	Our analytics personnel show superior understanding of technological trends.
BDAPC 6	Our analytics personnel show superior ability to learn new technologies.
BDAPC 7	Our analytics personnel are very knowledgeable about the critical factors for the success of our organization.
BDAPC 8	Our analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end.
BDAPC 9	Our analytics personnel understand our organization's policies and plans at a very high level.
BDAPC 10	Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions.
BDAPC 11	Our analytics personnel are very knowledgeable about business functions.
BDAPC 12	Our analytics personnel are very knowledgeable about the business environment.
BDAPC 13	Our analytics personnel are very capable in terms of planning, organizing, and leading projects.
BDAPC 14	Our analytics personnel are very capable in terms of planning and executing work in a collective environment.
BDAPC 15	Our analytics personnel are very capable in terms of teaching others.
BDAPC 16	Our analytics personnel work closely with customers and maintain productive user/client.
KE1	In this business unit, we meet with customers at least once a year to find out what products or services they will need in the future.
KE2	The company is in touch with professionals and expert technicians.
KE3	In this business unit, we do a lot of in-house market exploitation research.
KE4	We poll end users at least once a year to assess the quality of products and services.
KE5	Our employees maintain frequent collaboration with customers to accomplish and/or improve products and services.
KE6	We are proactive in managing outward knowledge flow.
KE7	We make exploitation it a formal practice to sell technological knowledge and intellectual property in the market knowledge exploitation.
KE8	We have a dedicated unit to commercialize knowledge assets.
KE9	We welcome others to purchase and use our technological knowledge or intellectual property.
KE10	We often exploit technological knowledge commercially and jointly with external organizations.
SI1	Our company develops products and services that have social impacts.
SI2	The value of our products and services is beneficial to society as a whole.
SI3	Our products and services serve both material and nonmaterial human needs.
SI4	Our company develops products and services that solve social problems.
SI5	Our products and services improve the standards of life.

Table 5 Construct measures validity and reliability analysis.

Reflective constructs		Items	Mean	Standard deviation	Factor loading	AVE	CR	References
Big Data Analytics Management Capability (BDAMC)	BDA Planning	BDAMC1	5.503	0.979	0.811	0.636	0.874	Akter et al. (2016)
		BDAMC2	5.599	1.036	0.775			
		BDAMC3	5.511	1.112	0.795			
		BDAMC4	5.621	1.126	0.809			
	BDA Investment	BDAMC5	5.503	1.038	0.837	0.630	0.872	
		BDAMC6	5.466	1.065	0.771			
		BDAMC7	5.494	1.016	0.796			
		BDAMC8	5.590	1.116	0.770			
	BDA Coordination	BDAMC9	5.415	1.134	0.772	0.524	0.812	
		BDAMC10	5.720	0.989	0.776			
		BDAMC11	5.514	1.076	0.785			
		BDAMC12	5.706	1.042	0.531			
	BDA Control	BDAMC13	5.655	1.101	0.774	0.583	0.848	
		BDAMC14	5.610	1.117	0.781			
		BDAMC15	5.672	1.109	0.798			
		BDAMC16	5.757	0.927	0.698			
Big Data Analytics Technology Capability (BDATC)	BDA Connectivity	BDATC1	5.616	1.111	0.802	0.616	0.865	Akter et al. (2016)
		BDATC2	5.582	1.202	0.806			
		BDATC3	5.644	1.031	0.778			
		BDATC4	5.153	1.428	0.753			
	BDA Compatibility	BDATC5	5.641	1.138	0.847	0.665	0.888	
		BDATC6	5.520	1.195	0.800			
		BDATC7	5.633	1.119	0.797			
		BDATC8	5.644	1.063	0.818			
	BDA Modularity	BDATC9	5.732	1.053	0.828	0.646	0.879	
		BDATC10	5.802	0.970	0.782			
		BDATC11	5.695	0.963	0.790			
		BDATC12	5.669	1.091	0.815			
Big Data Analytics Personnel Capability (BDAPC)	BDA Technology Management Knowledge	BDAPC1	5.884	0.979	0.833	0.608	0.861	Akter et al. (2016)
		BDAPC 2	5.774	0.967	0.765			
		BDAPC 3	5.915	1.037	0.722			
		BDAPC 4	5.825	0.989	0.797			
	BDA Technical Knowledge	BDAPC 5	5.732	0.981	0.838	0.639	0.876	
		BDAPC 6	5.788	1.034	0.783			
		BDAPC 7	5.701	1.024	0.785			
		BDAPC 8	5.686	1.027	0.792			
	BDA Business Knowledge	BDAPC 9	5.873	0.995	0.792	0.622	0.868	
		BDAPC 10	5.966	0.867	0.813			
		BDAPC 11	5.862	0.955	0.756			
		BDAPC 12	5.754	1.004	0.795			
	BDA Relational Knowledge	BDAPC 13	5.706	1.040	0.824	0.584	0.848	
		BDAPC 14	5.695	0.992	0.803			
		BDAPC 15	5.653	1.183	0.727			
		BDAPC 16	5.901	0.963	0.697			
Social innovation		SI1	5.791	0.956	0.726	0.591	0.878	Adomako and Tran (2022)
		SI2	5.944	1.003	0.747			
		SI3	5.732	0.984	0.769			
		SI4	5.856	0.949	0.795			
		SI5	5.768	0.997	0.803			
Knowledge exploration		KE1	5.799	1.047	0.755	0.608	0.885	Cegarra-Navarro et al. (2011)
		KE2	5.808	1.068	0.817			
		KE3	5.647	1.140	0.735			
		KE4	5.847	1.029	0.798			
		KE5	5.681	1.079	0.790			
Knowledge exploitation		KE6	5.853	0.950	0.783	0.588	0.877	Arias-Pérez et al. (2021)
		KE7	5.554	1.180	0.737			
		KE8	5.706	1.077	0.777			
		KE9	5.887	1.111	0.769			
		KE10	5.856	1.001	0.766			

exploitation play an important positive role in social innovation. In order to verify the mediating role of knowledge exploration and knowledge exploitation, we used the Bootstrap mediation effect in SPSS to test it. The results in Table 9 show that the indirect effects of big data analytics management capabilities, big data analytics technology capabilities, and big data analytics personnel capabilities on social innovation through knowledge exploration and knowledge exploitation are all free of 0 in the 95% confidence interval. This suggests that knowledge exploration and knowledge exploitation mediate the impact of big data

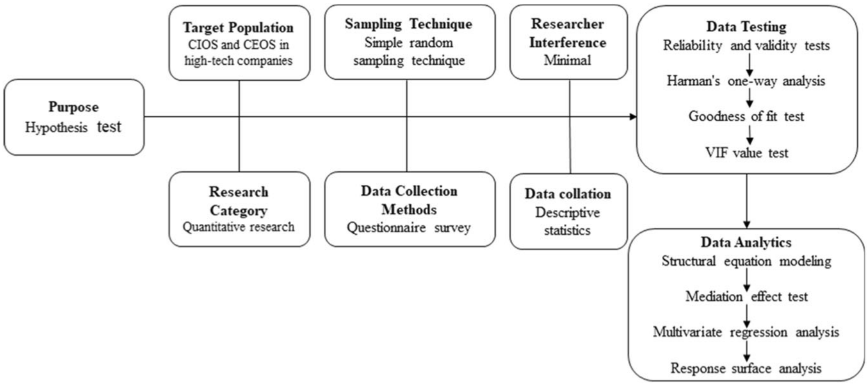

Fig. 3 Research procedure.

Table 6 Reliability and validity analysis.

Constructs	CR	AVE	Cronbach's α	KMO
Big Data Analytics Management Capability	0.957	0.593	0.891	0.924
Big Data Analytics Technology Capability	0.955	0.642	0.890	0.920
Big Data Analytics Personnel Capability	0.962	0.614	0.900	0.920
Social Innovation	0.878	0.591	0.826	0.766
Knowledge Exploration	0.885	0.608	0.837	0.854
Knowledge Exploitation	0.877	0.588	0.822	0.836

analytics management capabilities, big data analytics technology capabilities, and big data analytics personnel capabilities on social innovation, and Hypotheses H5a, H6a, H5b, H6b, H5c, and H6c are also supported.

Matching consistency verification. We examined the sample proportion situation. It discovered that the percentage of samples with consistent knowledge exploration and knowledge exploitation was 50%. And the percentage of samples with inconsistent sample proportions of "high knowledge exploitation-low knowledge exploration" and "high knowledge exploration-low knowledge exploitation" were 23.2% and 26.8%, respectively, which met the criteria for polynomial regression. Equation (1) below is the polynomial regression equation applied in this study, which includes the higher-order term of the two predictors (knowledge exploration and knowledge exploitation), and the square term of the predictor variables and their product (Yao and Ma, 2023).

$$\begin{aligned} Social\ Innovation = b_0 + b_1 knowledge\ exploration \\ + b_2 knowledge\ exploitation \\ + b_3 knowledge\ exploration^2 \\ + b_4 knowledge\ exploration \\ \times knowledge\ exploitation \\ + b_5 knowledge\ exploitation^2 + e \end{aligned} \tag{1}$$

As in Table 10, the slope of the response surface along the knowledge exploration and knowledge exploitation consistency line is significantly higher than 0 (slope = 0.634, $p < 0.001$), and the curvature are not significant. It indicated that "high knowledge exploration-high knowledge exploitation" is promoting social innovation when knowledge exploration and knowledge exploitation are consistent. Hypothesis H7a is supported. As can be seen in Fig. 5, the higher levels of social innovation are at the back corner of the figure among the fit line of Y = X where knowledge exploration and knowledge exploitation are both high. When Y = −X, the response surface slope and Curvature along the inconsistency line are significantly negative correlated (slope = −0.202, $p < 0.05$, Curvature = −0.204, $p < 0.001$). This shows that social innovation will decrease after knowledge exploration and knowledge exploitation change from a balanced match to an unbalanced match. H7b was supported. Moreover, as can be seen from Fig. 5, when the difference of knowledge exploitation is greater than that of knowledge exploration, the degree of social innovation is relatively higher.

Discussions and implications

Although it has been documented that organizations can use big data analytics capabilities to promote product innovation and performance (e.g., Ciampi et al., 2021; Ma et al., 2015; Mikalef et al., 2019; Wamba et al., 2017), little is known how big data analytics capabilities affects social innovation and what is the internal mechanism. This study examines the impact of big data analytics capabilities on social innovation and the mediating role of knowledge ambidexterity with a sample of 354 high-tech companies, and further examines the joint influence of knowledge exploration and knowledge exploitation on social innovation. The result show that big data analytics management capabilities, big data analytics technology capabilities, and big data analytics personnel capabilities all have a significant positive impact on social innovation, which provides empirical evidence for the use of big data analytics capabilities to facilitate social innovation (Calic and Ghasemaghaei, 2021; Maiolini et al., 2016), that is, social innovation can be achieved by increasing big data analytics management capabilities, big data analytics technology capabilities and big data analytics personnel capabilities to enhance the efficiency of social innovation while reducing costs and resource consumption, and to gain access to new information and data needed for social innovation. Second, based on the organizational learning theory and the organizational information processing theory, this study proposes a mediated model on the impact of big data analytics capabilities on social innovation, and the empirical results show that knowledge exploration and knowledge exploitation play a mediating role in big data analytics capabilities and social innovation, further emphasizing the importance of knowledge management in big data analytics capabilities and innovation (Mikalef et al., 2019). Big data analytics capabilities can help enhance knowledge exploration and knowledge exploitation to obtain relevant information through joint exploration of new knowledge and exploitation of existing knowledge, increasing the success rate of social innovation. Finally, the response surface analysis shows that the impact of high knowledge exploration – high knowledge exploitation on social innovation is greater than that of low knowledge

Table 7 Descriptive statistics and correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Age	-																
Category	−0.048	-															
Size	0.324**	0.037	-														
Big Data Analytics Planning	−0.013	−0.003	0.048	**0.797**													
Big Data Analytics Investment	−0.008	−0.007	0.092	0.556**	**0.794**												
Big Data Analytics Coordination	−0.063	−0.070	0.048	0.468**	0.639**	**0.780**											
Big Data Analytics Control	−0.08	−0.119*	0.053	0.384**	0.493**	0.507**	**0.763**										
Big Data Analytics Connectivity	−0.008	−0.017	0.095	0.336**	0.360**	0.358**	0.274**	**0.785**									
Big Data Analytics Compatibility	−0.037	−0.045	0.056	0.304**	0.354**	0.346**	0.295**	0.570**	**0.815**								
Big Data Analytics Modularity	0.083	−0.155**	0.148**	0.254**	0.347**	0.362**	0.313**	0.573**	0.540**	**0.804**							
Big Data Analytics Technology Management Knowledge	0.037	−0.076	0.046	0.275**	0.344**	0.360**	0.307**	0.334**	0.380**	0.335**	**0.780**						
Big Data Analytics Technical Knowledge	−0.027	−0.089	0.118*	0.292**	0.361**	0.349**	0.281**	0.357**	0.392**	0.404**	0.577**	**0.799**					
Big Data Analytics Business Knowledge	0.009	−0.012	0.091	0.289**	0.295**	0.248**	0.239**	0.261**	0.287**	0.303**	0.475**	0.584**	**0.789**				
Big Data Analytics Relational Knowledge	0.039	−0.178**	0.123*	0.258**	0.307**	0.351**	0.246**	0.315**	0.329**	0.326**	0.502**	0.601**	0.551**	**0.764**			
Social Innovation	−0.029	−0.040	0.050	0.414**	0.410**	0.389**	0.379**	0.427**	0.464**	0.434**	0.485**	0.521**	0.384**	0.433**	**0.769**		
Knowledge Exploration	0.109*	−0.069	0.085	0.234**	0.334**	0.299**	0.295**	0.311**	0.415**	0.388**	0.328**	0.344**	0.321**	0.325**	0.416**	**0.780**	
Knowledge Exploitation	−0.015	−0.120*	0.094	0.337**	0.365**	0.365**	0.285**	0.439**	0.376**	0.418**	0.422**	0.507**	0.376**	0.467**	0.540**	0.233**	**0.767**
Mean	2.853	3.91	3.226	5.559	5.513	5.589	5.674	5.499	5.609	5.725	5.847	5.727	5.864	5.739	5.818	5.756	5.771
SD	1.127	1.904	1.093	0.848	0.840	0.828	0.776	0.937	0.921	0.820	0.779	0.812	0.754	0.797	0.751	0.835	0.815

$N = 354$; $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 8 The results of structural equation modeling.

Hypothesis	Structural paths	Effect	S.E.	C.R.	Relationship
H1a	Big Data Analytics Management Capability→Social Innovation	0.194**	0.06	3.214	Supported
H1b	Big Data Analytics Technology Capability→Social Innovation	0.161**	0.053	3.022	Supported
H1c	Big Data Analytics Personnel Capability→Social Innovation	0.299***	0.078	3.854	Supported
H2a	Big Data Analytics Management Capability→Knowledge Exploration	0.217**	0.074	2.955	Supported
H2b	Big Data Analytics Technology Capability→Knowledge Exploration	0.315***	0.061	5.138	Supported
H2c	Big Data Analytics Personnel Capability→Knowledge Exploration	0.295***	0.076	3.867	Supported
H3a	Big Data Analytics Management Capability→Knowledge Exploitation	0.194**	0.065	2.996	Supported
H3b	Big Data Analytics Technology Capability→Knowledge Exploitation	0.265***	0.053	4.977	Supported
H3c	Big Data Analytics Personnel Capability→Knowledge Exploitation	0.557***	0.079	7.045	Supported
H4a	Knowledge Exploration→Social Innovation	0.134*	0.055	2.439	Supported
H4b	Knowledge Exploitation→Social Innovation	0.252***	0.074	3.393	Supported

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

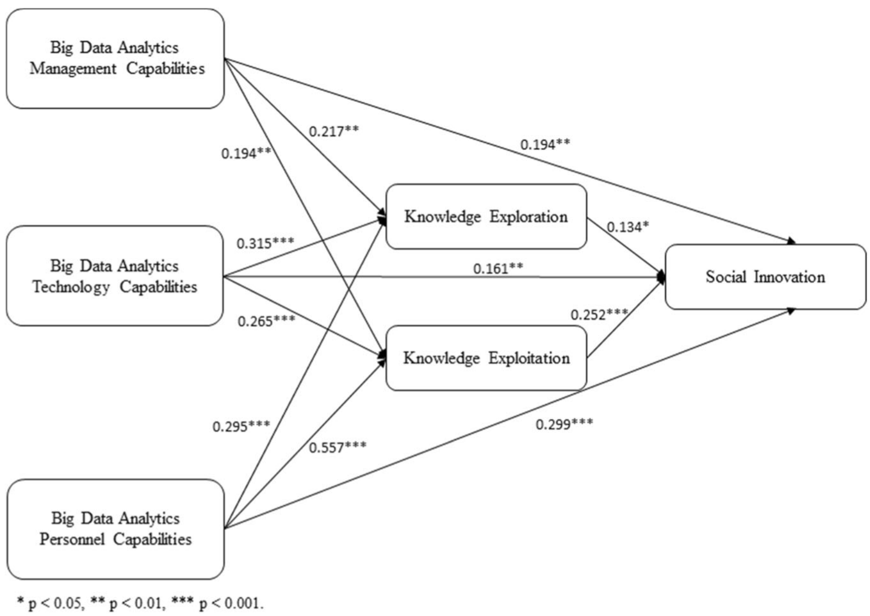

Fig. 4 Path analysis diagram.

exploration-low knowledge exploitation. When there is an imbalance between knowledge exploration and knowledge exploitation, the imbalance will lead to the decrease of social innovation. This study develops a perspective to investigate the impact of balanced and unbalanced match between knowledge exploration and knowledge exploitation on social innovation, and thus expands the research on knowledge exploration and knowledge exploitation in social innovation. The findings highlight the importance of knowledge exploration and knowledge exploitation in the process of social innovation.

Theoretical implications. This study contributes to the literature on big data analytics capabilities, knowledge ambidexterity, and social innovation. First, this study is the first to empirically investigate the relationship between big data analytics capabilities and social innovation based on the organizational information processing theory theory and the results show a significant positive relationship between big data analytics capabilities and social innovation, which thus enriches the study of social innovation in the digital age. Previous studies have mainly explored the impact of corporate factors, social factors and technical factors (Gasparin et al., 2021; Ho and Yoon, 2022; Mirvis et al., 2016) on social innovation through theoretical discussions or case studies, but there lacks empirical exploration of the development of social innovation in the big-data based digital context. With the advent of the Industry 4.0 era, more organization are focusing on the use of big data analytics to create new ideas to optimize social relationships and solve social problems (Herrera, 2015, Maiolini et al., 2016). Therefore, this study responds to the call for a better understanding of the role big data analytics capabilities in promoting social innovation (Maiolini et al., 2016), and the findings help enrich current innovation management theory on social innovation with a new big data analytics capabilities perspective.

Second, our study explores the mediating role of knowledge exploration and knowledge exploitation in the relationship between big data analytics capabilities and social innovation based on the organizational learning theory, which helps reveal the black box of big data analytics capabilities and social innovation. Previous research on big data analytics capabilities and innovation have been primarily based on dynamic capabilities theory and resource-base view (Al-Khatib, 2022; Bhatti et al., 2022; Ciampi et al., 2021; Mikalef et al., 2019; Su et al., 2022), and using an organizational learning perspective to explore the impact of knowledge exploration and knowledge exploitation on social innovation is in dearth. There has been evidence for the importance of knowledge ambidexterity for innovation research

Table 9 Mediation effect test.

Intermediary Path	Effects	95% confidence interval	
		LLCI	ULCI
Big Data Analytics Management Capability - Knowledge Exploration - Social Innovation	0.023	0.003	0.052
Big Data Analytics Management Capability - Knowledge Exploitation - Social Innovation	0.036	0.006	0.073
Big Data Analytics Technology Capability - Knowledge Exploration - Social Innovation	0.039	0.010	0.074
Big Data Analytics Technology Capability - Knowledge Exploitation - Social Innovation	0.063	0.026	0.110
Big Data Analytics Personnel Capability- Knowledge Exploration - Social Innovation	0.035	0.007	0.077
Big Data Analytics Personnel Capability- Knowledge Exploitation - Social Innovation	0.101	0.044	0.171

Table 10 Polynomial modeling and response surface analysis.

Variables	Social innovation
Constant	6.154***
Age	−0.028
Size	−0.015
Electronic communication industry	−0.143
Software service industry	−0.206
Biomedical industry	−0.118
Machinery manufacturing industry	−0.097
Education industry	−0.290*
Internet industry	−0.161
Knowledge Exploration	0.216***
Knowledge Exploitation	0.418***
Knowledge Exploration * Knowledge Exploration	−0.075**
Knowledge Exploration * Knowledge Exploitation	0.087
Knowledge Exploitation * Knowledge Exploitation	−0.042
F	18.415***
R^2	0.413
ΔR^2	0.022**
Perfect balance line	
Slope1	0.634***
Curvature1	−0.030
Perfect imbalance line	
Slope2	−0.202*
Curvature2	−0.204***

$N = 354$; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(Li et al., 2018), and one of the key reasons for the slow growth of new social enterprises is the inefficiency of an effective knowledge management process (Maalaoui et al., 2020), yet the evidence on the impact of knowledge exploration and knowledge exploitation on social innovation is not sufficient (Maalaoui et al., 2020). This study explicitly explores how knowledge exploration and knowledge exploitation contribute to social innovation and how they mediate the relationship between big data analytics capabilities and social innovation by identifying the path from big data analytics capabilities to social innovation, which thus bridges the gap in existing research, and also provides a new view, on the impact of big data analytics capabilities on organizational development.

Furthermore, our study also explores the impact of different configurations of knowledge exploration and knowledge exploitation on social innovation from the perspective of capability complementarity. Previous studies have focused on the isolated impact of knowledge ambidexterity on innovation (Benitez et al., 2018). However, knowledge exploration and knowledge exploitation do not operate independently in most cases, and their complex configuration can either reinforce or counteract each other's impact (Arias-Pérez et al., 2021; Dezi et al., 2021). The joint impact of appropriate configurations of knowledge exploration and knowledge exploitation has been rarely discussed in previous studies. This study fills this research gap by empirically examining how knowledge exploration and knowledge exploitation interact with each other to influence social innovation and demonstrates that proper synergies between knowledge exploration and knowledge exploitation contributes more to social innovation.

Managerial implications. Our study also has important implications in managerial practices. First, our study shows that big data analytics capabilities including big data analytics management capabilities, big data analytics technology capabilities, and big data analytics personnel capabilities all positively affect social innovation. Following these findings and considering the increased concerns with social issues in the global economy, organizations can develop stronger big data analytics capabilities to promote social innovation more effectively. On the one hand, organizations are encouraged to build a big data-driven culture within the organization and cultivate valuable big data analytics capabilities at the managerial levels throughout the organization for better big data analytics management capabilities. On the other hand, organizations can actively develop big data analytics technology capabilities by investing in big data technologies to accelerate advancement of big data analytics technologies and thus enhance their ability to conduct social innovation. In addition, organizations should recruit and train big data analytics staff to develop big data analytics personnel capabilities so as to improve their ability to use big data analytics to solve social issues and promote social innovation.

Second, organizations should focus on knowledge management development in their efforts to booster social innovation. Our study shows that knowledge exploration and knowledge exploitation play an important role in relating the influence of big data analytics capabilities to social innovation, which points to an important implication: developing stronger knowledge management capabilities to facilitate social innovation. This can be done by putting more efforts to explore new ideas and information from outside the organizations and to exploit internal knowledge stocks to improve efficiency and quality, both of which can facilitate the process of social innovation.

Third, in addition to realizing the important role of knowledge management in promoting social invocation in organizations and thus investing more in knowledge management, managerial practitioners should also focus on striking a balance of knowledge exploration and knowledge exploitation. The response surface analysis shows that it is clear that organizations should not only encourage R&D staff to strengthen the interactions with external knowledge networks and cooperate with external partners such as universities, governments, and customers to acquire information and knowledge to enrich their own knowledge base, but also they should effectively exploit internal knowledge to combine with new knowledge for innovation, transforming knowledge into social innovation, a joint effect on innovations to complex social issues.

More importantly, managers should be cautious with the trap of knowledge exploration and exploitation mismatch and its

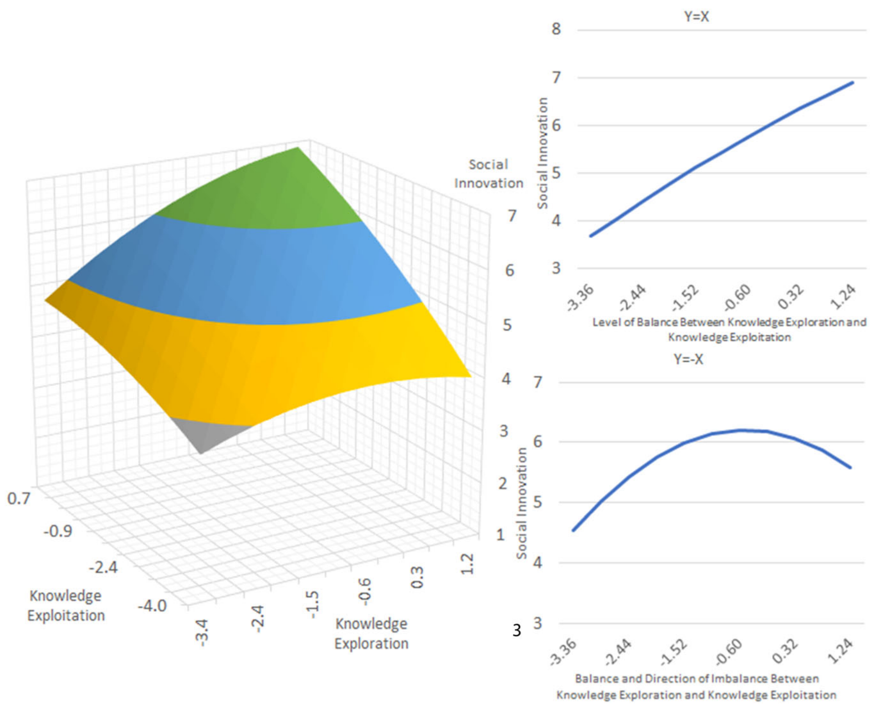

Fig. 5 Response surface analysis.

impact on social innovation. Overly relying on or ignoring either kind of knowledge ambidexterity is detrimental to social innovation. It is crucial that organizations maintain a balanced position in their knowledge management strategies: a match between knowledge exploration and knowledge exploitation is much more important. When an organization is unable to pursue and maintain knowledge exploration and knowledge exploitation at a balanced level, the priority should be given to knowledge exploitation over knowledge exploration. This is because social innovation is relatively high when knowledge exploitation is greater than knowledge exploration (Shanock et al., 2010).

Limitations and future research. Although our study has the potential to make important contributions to the literature on big data analytics capabilities and social innovation and also to managerial practices for better organizational development, it is important to understand the limitations in generalizing the findings. First, the data gathered are solely reflective of Chinese scenario and cannot be generalized without careful considerations because this study is exclusively based on Chinese companies with big data analytics capabilities and social innovation. A cross-country analysis should be conducted in the future in order to determine whether the current results are applicable to other countries. Second, this study examined the mediating role of knowledge exploration and knowledge exploitation between big data analytics capabilities and social innovation. However, there are still other variables that could affect the process, and future studies can investigate other variables such as strategic orientation for their mediating effect between big data analytics capabilities and social innovation. Finally, we used questionnaires to collect data, but the questionnaire data contained some subjective factors. Future studies could analyze objective data from enterprise reports to improve data objectivity and external validity.

Data availability

The data are available from the corresponding author on reasonable request.

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Author contributions

Conceptualization, WN; methodology, CBL; software, WLY; validation, WLY, and PS; writing—original draft preparation, CBL; writing—review and editing, WN and MZZ. All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This study is exempted in line with the School of Business at Beijing Technology and Business University ethical guidelines as per the Declaration of Helsinki, ensuring participant anonymity and avoiding sensitive topics. Informed consent was obtained during data collection from January to March 2022 and March to May 2023, detailing purpose, data use, and risks, emphasizing voluntary participation. This reflects our commitment to ethical standards, prioritizing participant rights and welfare. Since the study exempted and any procedures requiring ethical approval by an institutional review board, no specific ethical approval number was assigned.

Informed consent

Informed consent was obtained from all individual participants included in the study.

Additional information

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