The effects of analytics and sensing capabilities on operational performance: The moderating role of a data-driven culture

Abstract: Studies indicate that organizational capability is a key factor in operational performance, and that both sensing capabilities and analytics capabilities have a significant influence on operational performance. This study develops a framework to examine the impact of organizational capability on operational performance, with a specific focus on the implementation of sensing and analytics capabilities. We combine strategic fit theory, the dynamic capability view, and the resource-based view to examine how micro, small, and medium enterprises (MSMEs) strategically integrate a data-driven culture (DDC) with their organizational capabilities to enhance operational performance. We carry out empirical research to investigate whether a DDC moderates the influence of organizational capability on operational performance. Structural equation modeling of survey data from 149 MSMEs reveals that both sensing and analytics capabilities have a positive impact on operational performance. The results also suggest that a DDC positively moderates the influence of organizational capability on operational performance. We discuss the theoretical and managerial implications of our findings, the limitations of the study, and opportunities for further research.

Keywords: Analytics capability, Data-driven culture, Operational performance; Sensing capability

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1. Introduction

Micro, small, and medium enterprises (MSMEs) make up over 90% of all firms across the world.[1] MSMEs in the manufacturing industry are responsible for a large proportion of global pollution and resource consumption. The definition of MSMEs varies across continents relative to the size of the domestic economy. In this study, we follow the Organisation for Economic Co-operation and Development and define MSMEs as firms with a maximum of 249 employees, which includes micro (1–9), small (10–49) and medium (50–249) enterprises (United Nations Report, 2020, p. 4).

Industry 4.0, big data analysis, optimization, logistics excellence, automation, digital transformation, and the circular economy have become buzzwords in modern economies. Industry 4.0 is changing the design and functioning of operations and supply chains. For example, block chain and the internet of things (IoT) now play a vital role in improving supply chain transparency and traceability. However, few empirical studies have explored the prospects and impact of Industry 4.0 on operations (Frederico et al., 2019). Operations management, which in the past was generally viewed as a horizontal function, has now become established as a form of vertical management with multiple branches (Gupta et al., 2013).

Modern operations managers must have insight into the alignment of operational strategies with organizational goals. Supply chain experts and business analysts must be able to predict the network design, quality norms, and impact of technology on business operations (Chae et al., 2014). Analytics now plays a vital role in operations management and decision-making (Choi et al., 2018), and the integration of operations and analytics optimizes processes.

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[1] https://www.un.org/en/observances/micro-small-medium-businesses-day

Analytics is also important to the circular economy, sustainable operations, and risk management (Mani et al., 2017).

In developing countries like China, one of the main issues for MSMEs is non-standardized output due to problems with the production process, conventional machinery, limited financial support, and a shortage of skilled labor, all of which lead to comparatively greater waste generation in terms of repairs and rejections, resulting in a loss of goodwill and profits (Gupta et al., 2019). The application of analytics and sensing capabilities can help MSMEs detect potential errors early, evaluate the causes of defects, and predict the number of reworks required to enhance operational performance (Sariyer et al., 2021).

This study has two objectives. The first is to examine the impact of organizational capability on operational performance, focusing on the implementation of analytics and sensing capabilities to enhance operational performance. The second objective is to investigate whether a data-driven culture (DDC) moderates the influence of organizational capability on operational performance. Accordingly, we address the following research questions:

Research question 1. How does organizational capability influence operational performance?

Research question 2. How does a DDC moderate the influence of organizational capability on operational performance?

The remainder of this paper proceeds as follows. Section 2 describes the theory and hypotheses and develops the research model. Section 3 outlines the research design and data collection methods. Section 4 presents the data analysis and results. Finally, Section 5 discusses

the theoretical contributions, managerial implications, limitations, and directions for future research.

2. Theory and hypotheses

2.1. MSMEs

MSMEs have helped accelerate economic development in Asia (Kamble et al., 2020). MSMEs face various challenges because of their constrained resources. In addition, many lack up-to-date technology and, as a result, either faced supply chain bottlenecks or collapsed during the COVID-19 pandemic (Bag et al., 2021; Modgil et al., 2021). Therefore, sustainability is a critical concern, especially for MSMEs that are highly vulnerable to uncertainty and risk (Behi et al., 2022). MSMEs urgently need to shift to digital technologies to survive. However, their inability to effectively and quickly migrate to the newest business models and technologies from traditional models and technologies makes it challenging for MSMEs to adopt digital technologies (Ritter & Pedersen, 2020). MSMEs must also build resilience by enhancing their ability to recognize market opportunities (Khurana et al., 2022). Analytics capability can help firms do this by allowing them to analyze large sets of data from diverse sources. Analytics capabilities allow MSMEs to control heterogeneous and vast data sets and assess the states of external markets and business units (Rialti et al., 2019). Analytics capabilities also allow MSMEs to collect data from social media platforms to analyze customer sentiments and behavior to help create new revenue streams.

2.2. Operational performance

Operational performance refers to "a firm's operational efficiency, which can help explain the firm's competitiveness and profitability in the market" (Hong et al., 2019, p. 228). Developing

a substantial predictive capability through big data analytics can help an organization to reap the greatest possible advantages, leading to higher operational performance (Gupta et al., 2020). Previous studies typically measure operations management using time, flexibility, quality, and cost (Neely et al., 1995). In this study, we apply the operational performance measures of Liu et al. (2016) to evaluate the operational benefits of the fit of a firm's resources to its environment. These measures comprise seven items that collectively assess the effects of sensing and analytics capabilities on process-related performance. They are commonly used to assess IT-enabled competitive advantages in empirical studies of information systems and operations management that apply the resource-based view (RBV) of the firm (Flynn et al., 2010; Rai et al., 2006; Wong et al., 2011).

Operational performance can be assessed using a variety of methods and measures. However, we focus specifically on a previously studied perspective: organizational capability. The main focus of organizational capability is identifying the critical determinants of a company's competitive advantage and performance (Krasnikov and Jayachandran, 2008).

Appendix A summarizes the main studies on the influence of organizational capability on business performance published in the past ten years. The reviewed works are classified by type of study, theory applied, author, and year, and the main findings of each study are listed. We find extensive use of the RBV (12 of 22 articles) and the dynamic capability view (DCV; 9 of 22 articles). Appendix B lists the articles included in our literature review.

2.3. Organizational capability

The focus of the RBV is the internal operations of a firm and its bundle of resources (Priem and Butler, 2001). This widely supported view (Barney, 2001) posits that firms with valuable,

non-substitutable, and scarce resources can obtain a sustainable competitive advantage. Organizational capability can be considered a resource (Lieberman and Montgomery, 1998), and researchers have found that organizational capability helps managers select meaningful organizational outputs (Von Alan et al., 2004; Winter, 2000). Organizational capability can be described as a firm's ability to transform inputs into outputs to create value (Chatterjee et al., 2015), and is a critical determinant of a company's performance and competitive advantage (Krasnikov and Jayachandran, 2008). In the hierarchy of capabilities conceptualized by Grant (1996), specialized knowledge comprises task-specific and activity-related capabilities at the lowest level. These capabilities are then integrated at the middle level into broad functional capabilities, such as R&D and manufacturing. At the highest level are cross-functional capabilities, such as innovation (Peng et al., 2008), collaboration (Allred et al., 2011), sensing capabilities (Vanpoucke et al., 2014), and analytics capabilities (Srinivasan and Swink, 2018). Studies indicate that sensing capabilities (Ngo et al., 2019) and analytics capabilities (Dubey et al., 2021; Fosso Wamba et al., 2020) are exerting an increasingly significant influence on business performance. However, the literature on the effect of sensing and analytics capabilities on operational performance is sparse, particularly in relation to a DDC in MSMEs. Therefore, this study contributes to the literature by offering a research model of the relationship between sensing and analytics capabilities and operational performance, and by illustrating the moderating facets of a DDC.

Our proposed conceptual model (see Figure 1) is based on the RBV and the idea that superior operational performance results from the best use of the sensing and analytics capabilities an organization possesses (Barney, 1986, 1991). Studies also suggest that a DDC plays a key role in shaping a firm's business analytics and competitive advantage (Chatterjee et al., 2021). Thus, our model incorporates a DDC to investigate its moderating effect on organizational capability and operational performance. Obtaining a strategic fit in a dynamic

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environment requires a DDC that allows the organization to accurately assess environmental changes, formulate responses, and reconfigure its internal resources. This is also consistent with the RBV of the firm (Barney, 1986, 1991, 2001) and is in line with the DCV of an organization's ability to determine the resources available to it and apply them effectively in a dynamic environment (e.g., Eisenhardt and Martin, 2000; Teece et al., 1997).

*** *Please insert Figure 1 about here* ***

2.3.1. Analytics capabilities

According to Wu et al. (2020), analytics capabilities refer to the ability to transform, analyze, and process data into useful information to support decision-making, provide useful insights, and reveal patterns that could be improved by digitization and artificial intelligence. Srinivasan and Swink (2018) further extended the definition of analytics capabilities, describing them as organizational facilities that encompass tools, processes, and techniques that enable an organization to process, visualize, analyze, and organize data to produce managerial insights that enable data-driven operational decision-making, operational planning, and execution. Analytics capabilities also enable firms to improve their information processing capabilities to collect data from different sources and analyze them to obtain managerial insights (Srinivasan and Swink, 2018). Companies combine these processes and tools to integrate, decompose, and combine information. Many firms are investing in different types of analytics capabilities to increase their operational performance, such as data analytics (Sariyer et al., 2021), business analytics (Krishnamoorthi and Mathew, 2018), information analytics (Park and Mithas, 2020), and big data analytics (Dubey et al., 2021). Analytics capabilities also enable firms to evaluate operational alternatives when there are changes in demand or supply shortages, and to develop resources and cost-saving measures to reduce the imbalance between supply and demand (Liu

et al., 2020). Therefore, we propose the following hypothesis:

H1: Analytics capabilities have a direct positive effect on operational performance.

2.3.2. Sensing capabilities

A firm's sensing capabilities refer to its ability to assess, develop, and identify technological opportunities that meet customers' needs and new business opportunities (Fosso Wamba et al., 2020). They also refer to a firm's ability to learn from the market environment and then take action based on its newly acquired knowledge (Fosso Wamba et al., 2020). Sensing capabilities include the generation and dissemination of market intelligence and ability to react to it (Jaworski and Kohli, 1993) to improve operational performance (Shin et al., 2015). Sensing capabilities are rooted in market development and organizational information processing activities such as evaluating, filtering, interpreting, and scanning information (Mu and Di Benedetto, 2011). These processing activities apply logic in volatile, unpredictable, and complex market environments to help firms perceive market opportunities and changes before they materialize (Day, 2011). For instance, American Airlines uses a decision-support system that works with its reservation system to enhance its sensing capabilities (Chi et al., 2010). Effective sensing capabilities yield nuanced, accurate, and diverse information that supports an understanding of the opportunities and threats facing a firm (Ballesteros et al., 2017). Such capabilities help keep a firm vigilant and alert to opportunities and market trends. Sensing capabilities are increased by deploying IT to transform informational resources into knowledge assets. Business intelligence systems can help continuously improve operational performance by discerning and receiving accurate, timely, and relevant information and data and then transforming and analyzing it to create new knowledge (Chen and Lin, 2021). For example, firms with superior IT-enabled sensing capabilities are able to adjust their internal operations

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in response to potential shifts in the business environment by closely monitoring their competitors' movements and customer feedback to inform appropriate operations management decisions (Mikalef and Pateli, 2017). Thus, we propose the following hypothesis:

H2: Sensing capabilities have a direct positive effect on operational performance.

2.4. DDC

Mikalef and Krogstie (2020, p. 262) suggest that a DDC is "a key factor in determining overall success and the alignment with organizational strategy." A DDC is defined (Kiron et al., 2013, p. 18) as "a pattern of behavior and practices by a group of people who share a belief that having, understanding, and using certain kinds of data and information plays a crucial role in the success of their organizations." Strategic fit theory suggests that developing organizational capability through strategic integration results in a competitive advantage and better performance (Kristianto et al., 2011). Performance can also be improved by establishing a good fit between a firm's environment and its resources (Kashan and Mohannak, 2017). Firms should try to match their resource deployment to their strategic requirements (Swink et al., 2005). A DDC combines organizational factors such as business processes, structures, regulation, and strategy to facilitate the application of business analytics (Cao and Duan, 2015). A firm with a DDC treats data as an intangible asset that has value to the firm (Kiron and Shockley, 2011), and creates an environment for management to make decisions that result in superior operational performance and efficiency and thus enhance competitiveness.

The RBV states that firms need to develop capabilities to gain a competitive advantage and overcome difficulties. However, this view fails to appropriately delineate the capabilities needed in dynamic environments. Further, it gives no clear explanation of why and how firms gain a competitive advantage in uncertain environments. The DCV fills this gap by promoting

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the organization with appropriate resources and capabilities to deal with situation-specific changes (Barney, 1991; Eisenhardt and Martin, 2000; Wernerfelt, 1984), thereby addressing contingencies. Moreover, it suggests that firms in dynamic environments should focus on improving their capabilities rather than merely exploiting specific resources to gain a competitive advantage (Teece et al., 1997). A DDC is a critical intangible resource (Zhu et al., 2021) that can be referred as "the extent to which organizational members (including top-level executives, middle managers, and low-level employees) make decisions based on the insights extracted from data" (Gupta and George, 2016, p. 1053). It is associated with assumptions, beliefs, and values that lead to organizational success (Chatterjee et al., 2021). In addition, a DDC helps companies improve performance by using data-based insights to take appropriate decisions. Firms can create a DDC by leveraging business analytics to gain a competitive advantage (Chatterjee et al., 2021). The three main types of analytics capabilities that improve operational performance are intangible resources, tangible resources, and human skills and knowledge. As an intangible resource (Zhu et al., 2021), a DDC may be an important variable moderating the relationship between analytics and sensing capabilities and operational performance. However, to the best of our knowledge, there are almost no reported studies that explore DDC as a moderator of this relationship. We therefore propose the following hypotheses:

H3a: A DDC has a moderating effect on the relationship between analytics capabilities and operational performance.

H3b: A DDC has a moderating effect on the relationship between sensing capabilities and operational performance.

2.5. Control variables

We control for firm size because this is correlated with operational performance (Psillaki et al., 2010). Small and micro firms face more challenges and need more support than medium or large firms due to their limited resources, which may influence operational performance (Lwesya et al., 2021). We also control for firm age, as years of business experience can also influence operational performance (Hsieh et al., 2010; Lwesya et al., 2021).

3. Research methodology

Our conceptual framework is founded on theoretical observations from the literature. We then examined the research model in a quantitative study (Weerawardena et al., 2015). The data were collected using a self-report survey instrument that was carefully developed using guidelines and exemplars in the operational management and information systems literature, for example, Srinivasan and Swink (2018) and Pavlou and El Sawy (2011).

3.1. Research design

We gathered our survey data exclusively from the food industry for several reasons. The world population is expected to reach more than nine billion by 2050, increasing the burden on world food production systems (Godfray et al., 2010). Traditionally, the food industry is considered slow-growing and mature compared with other industries (Santoro et al., 2017). The industry faces various challenges, including greater competition and disruptive technologies such as big data and the internet of things (Ferraris et al., 2020). For hundreds of years, information has been vital to the food industry (Godfray et al., 2010), which has long been recognized as a data-driven industry (Serazetdinova et al., 2019). Information and data collected from competitors and consumers allow the industry to determine current and future production trends (Chapman et al., 2021).

We first interviewed six managers in the industry to check their understanding of the items in our questionnaire. We then clarified and reformulated certain items to make them more understandable. Finally, this instrument was used to collect survey data from supply chain managers in the food industry via online questionnaires (Lee and Xia, 2010).

3.2. Research method

The survey data were collected from the food industry in Shanghai, China. The sample included food producers, food processors, wholesalers, retailers, and restaurants. We chose Chinese food companies because of their unique characteristics, including a lack of standardization of services and products, the diversity of services and products available, the dominance of MSMEs in the industry, and the presence of a large market (Hong et al., 2021). Although Shanghai is one of China's most modern cities (Liu et al., 2018), consumers do not rate its food safety highly (food safety satisfaction score (2020) = 86.5%), [2] indicating that there is significant room for improvement. Furthermore, China has experienced many food safety scandals in recent years, such as fake and sub-standard milk powder (Tam and Yang, 2005), poisonous wine (Bai et al., 2007), fake eggs (Yan, 2012), and fake soy sauce (Liu et al., 2015). Chinese food firms with a good understanding of analytics capabilities can improve their operational performance by reducing product recalls and financial losses. Data analytics monitoring allows firms to proactively maintain a consistently high standard of data quality through routine data monitoring. Furthermore, firms with good sensing capabilities can screen the external environment and respond in a timely manner to consumer complaints.

The profile of the respondents is shown in Appendix C. All of the firms surveyed were MSMEs with a maximum of 249 employees (United Nations Report, 2020, p. 4). Of the 710 respondents invited to complete the survey, 157 returned completed surveys, giving a response rate of 22.1%, which is acceptable in business research (Malhotra et al., 2002). Checking revealed 8 unusable surveys due to unrealistic responses, resulting in a final sample of 149 (an acceptable response rate of 21%).

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[2] http://www.gov.cn/xinwen/2021-01/28/content_5583206.htm

3.3. Measurement issues

We used several procedures to minimize common method variance. First, multiple items were used to measure each construct to help dissipate any short-term memory effect associated with the previous scale (Harrison et al. 1996). Second, to ensure face validity, we used distinctive constructs (Harrison et al. 1996). Third, the possibility of common method variance was evaluated using Harman's single-factor test (Harman, 1976). A five-factor solution (with eigenvalues >1.0) was generated. The most covariance explained by one factor was 36.1%, indicating that common method variance is unlikely to have confounded our results (Podsakoff and Organ, 1986).

3.4. Measures

We measured analytics capabilities using the five-item measure of Srinivasan and Swink (2018), and sensing capabilities using a four-item measure based on Pavlou and El Sawy (2011). DDC was measured with a four-item measure based on Zhang et al. (2020), and operational performance with a seven-item measure based on Liu et al. (2016). Firm size was measured as the number of employees in the firm at time of the survey (Tang and Konde, 2020), and firm age by the number of years since the firm was founded (Tang and Konde, 2020). Appendix D shows the measurement items.

4. Data analysis and results

4.1. Measurement validation

We followed the steps of Anderson and Gerbing (1998) to purify the construct measures and assess their convergent and discriminate validity. First, the measurement item to total correlations were tested. As noted in Table 1, each item loaded strongly on the expected factor (all loadings were greater than 0.63). Second, exploratory factor analysis with varimax rotation (see Table 2) was used to assess the discriminant and internal factor validity. As noted in Table 2, all items had greater loadings on their own construct than on the other constructs of the model. Third, Cronbach's alpha was tested for each construct, and the composite reliability values all exceeded the recommended 0.70 cut-off (Nunnally, 1978; see Table 3). Finally, as shown in Table 3, the constructs had more variance with their own measures than with the other constructs of the model, confirming their discriminant validity. The percentage of variance captured by a construct was represented by the average variance extracted (AVE; Bassellier and Benbasat, 2004). According to Chin (1998), the square root of the AVE for each construct should be greater than its correlation with other factors. All of the constructs had adequate discriminant validity and sufficient reliability (Gefen et al., 2000; Liang et al., 2007).

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4.2. Test of the structural model

We evaluated our data using the partial least squares (PLS) structural equation modelling method (Hair et al., 2011). The PLS results are shown in Figure 2. Analytics capabilities had a significant positive effect (0.274, $p < 0.05$) on operational performance, supporting H1. Similarly, sensing capabilities had a significant positive effect (0.360, $p < 0.05$) on operational performance, supporting H2. DDC significantly moderated (0.015, $p < 0.1$) the effect of analytics capabilities on operational performance, supporting H3a. Similarly, DDC significantly moderated (0.051, $p < 0.05$) the effect of sensing capabilities on operational performance, supporting H3b. Firm size had a significant positive effect (0.018, $p < 0.1$) on operational performance, indicating that larger firms can benefit from improved analytics and sensing capabilities for superior performance. Firm age positively affected performance (0.082, $p < 0.01$), probably because managerial practices and expertise improve over time as knowledge accumulates through learning by doing. This can improve a firm's problem-solving and analytics capabilities, resulting in better business planning to cope with uncertainty. In addition, older firms tend to have stronger networks and sensing capabilities due to their well-established relationships with customers, governments, communities, financial institutions, suppliers, and business partners, and have a reputation in the market (Tang and Konde, 2020).

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5. Discussion and conclusions

5.1. Discussion of findings

Our study demonstrates the influence of sensing and analytics capabilities on the operational performance of MSMEs. Our results show that sensing and analytics capabilities significantly improve operational performance in the Chinese food industry. As most food manufacturing processes in China are highly automated due to hygiene and quality assurance concerns, analytics capabilities play a significant role in improving and automating manufacturing processes (Park and Mithas, 2020). In addition, sensing capabilities provide firms with accurate and timely information and data relevant to decision-making, which is especially important for MSMEs due to their limited resources.

Second, the results show that a DDC moderates the effect of sensing capabilities on operational performance, probably because data-driven decisions are better informed and thus more effective (Zhan et al., 2018), especially for MSMEs. In addition, a DDC speeds up the sensing of market changes, avoiding over-stocking and financial burdens, especially for perishable items (Maheshwari et al., 2021). Due to their size advantage, MSMEs can make faster decisions on producing desirable items driven by consumer feedback data. All of these factors can help improve operational performance.

Third, our results show that a DDC moderates the effect of analytics capabilities on operational performance, possibly because data-driven operational decision-making, operational planning, and execution are enabled and more effective in such a culture (Yan et al., 2021). In MSMEs in the food industry, the improper maintenance of perishable items such as a lack of infrastructure, poor collaboration, the improper handling of units, outdated storage facilities, and poor storage systems leads to great financial losses (Sharon et al., 2014). However, MSMEs can now detect such problems easily by analyzing current data and using it

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to improve the performance of food production lines and food storage systems.

5.2. Contributions to theory

Our results make several theoretical contributions to the field. First, previous studies have demonstrated that analytics capabilities and sensing capabilities are important determinants of firm performance (Fosso Wamba et al., 2020; Dubey et al., 2021). Our study provides empirical evidence of the importance of these two capabilities specifically to food companies in that they enable firms to deliver safe, reliable, high-quality products to consumers. This is especially relevant to Chinese food companies, which face intense pressure to ensure food safety (Jen, 2018), and the need to enhance operational performance has become more critical during the COVID-19 pandemic. To the best of our knowledge, this is the first study to provide empirical evidence of the benefits of analytics and sensing capabilities for the operational performance of MSMEs in the food industry.

Second, our research contributes to the literature on DDC. Most research on the influence of organizational capability on operational performance overlooks the effect of a DDC on this relationship. Our empirical results show that a DDC positively moderates the influence of organizational capability on operational performance. By providing a data-driven environment, managers of MSMEs are able to make decisions based on factual data rather than opinion. Given the limited financial resources of MSMEs, cost-effectiveness is salient. Managers should therefore promote a DDC in their firms and use open-source analytical and sensing software to assist sensing and analytical tasks.

Third, MSMEs need to be flexible and agile and have dynamic capabilities in the competitive environment of the big data era (Sariyer et al., 2021). Recent technological advancements enable firms to identify market opportunities to gain competitive advantages

(Khurana et al., 2022). In addition, MSMEs need big data analytics capabilities to collect, store, manage, and transform raw data into useful and actionable knowledge (Kiron et al., 2014; Bumblauskas et al., 2017). Based on the RBV and DCV, this study makes theoretical contributions by proposing a research model for the effects of sensing and analytics capabilities in the dynamic environments of MSMEs. Using survey data from 149 Chinese senior executives in MSMEs in the food industry, we empirically explore the relationship between a firm's sensing and analytics capabilities and operational performance. This study makes an important contribution to the information systems and operations management literature by showing how sensing and analytics capabilities improve a firm's operational performance.

Fourth, our results support the use of the RBV, DCV, and strategic fit theory to understand the moderating effects of a DDC on organizational capability and performance in MSMEs. A DDC is considered a vital resource that supports other firm capabilities (Fosso Wamba et al., 2020). Firms in dynamic environments need to develop a DDC to raise performance by using business analytics (Wang et al., 2020). Thus, in this work, we extend the strategic fit theory by integrating DDC into the conceptual model of organizational capability and operational performance. We show that superior operational performance for MSMEs can be achieved by establishing a good fit between a firm's environment and its DDC. The success of an MSME depends on its ability to obtain non-substitutable, rare, inimitable, and valuable data.

5.3. Managerial implications

Our study yields several implications for managers seeking superior operational performance. First, global supply chains have been made vulnerable by the COVID-19 pandemic, as many government agencies across the world have restricted exports and imports to reduce the spread of the disease. Firms' production capabilities have also decreased substantially due to delays

in resuming work. Extreme stress has been placed on the food service industry following decreasing prices during the pandemic. MSMEs are now required to produce better quality and cheaper goods more quickly to maintain current profits. The model developed in this study can help practitioners achieve these aims.

Second, organizations should develop a DDC that fits their environment. Managers need to become aware that a DDC is a catalyst for converting investments in sensing and analytics capabilities into business value (Zhu et al., 2021).

Third, when prioritizing constrained resources, managers of MSMEs should focus on developing their firm's sensing capabilities. For example, the COVID-19 pandemic caused various difficulties for MSMEs, such as order cancellations, constrained cash flows, and a lack of organization-level communication. Overcoming these issues required the ability to sense business opportunities at the organizational level, to understand what was happening within organizations, and to learn from both external and internal sources (Khurana et al., 2022). Sensing capabilities help MSMEs retain clients and attract new customers by highlighting customers' needs, allowing firms to modify products to match changing customer requirements and preferences. For example, analyzing the text and sentiment in customers' social media posts can help identify customer preferences, from which firms can identify new opportunities (Huang et al., 2020).

Fourth, MSMEs need to develop analytics capabilities because of their resource constraints (Shafiq et al., 2020). For example, MSMEs need to synergistically and strategically deploy limited resources for both operations and business development. MSMEs can more accurately match their resources to potential business opportunities if they have strong big data analytics capabilities (Mikalef et al., 2020). Big data analytics capabilities enable MSMEs to use data-driven decision-making to exploit, combine, and coordinate their constrained

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resources to avoid environmental or external market threats and take advantage of valuable opportunities to grow (Zheng et al., 2022).

5.4. Limitations and future research

This study has several limitations. As we investigated the food supply chain in Shanghai (China), our findings may not be generalizable to other industries or countries. In addition, we only studied the influence of cross-functional capabilities (i.e., analytics and sensing capabilities) on operational performance. However, capabilities in specific areas such as R&D and manufacturing also can affect performance (Nystrom et al., 2002). The data were collected in China, and although it is an important food supply chain, the results may not be fully generalizable to other Asian or Western countries. We acknowledge these limitations, which future studies could investigate further.

Furthermore, the conceptual framework and research model in this study focus on a DDC in the supply chain context, but several other domains deserve investigation in future studies. For example, fruitful findings could be obtained by exploring a DDC in other settings, industries, and types of organizations. Such research would also help to validate the framework and research model presented here and enhance its generalizability. The managerial and theoretical development of a DDC is also a rich topic for future studies; for example, it would be interesting to study the moderating role of a DDC in the relationship between data-driven innovations and firm performance. We expect new approaches to the topic to emerge from further critical reviews, examinations, and investigations.

5.5. Conclusions

We obtained evidence through a survey study of 149 MSMEs in China's food industry on the influence of sensing and analytics capabilities on operational performance and how a DDC moderates that influence. Our findings confirm our hypothesis that sensing and analytics capabilities directly improve operational performance. We also found that a DDC positively moderates the influence of sensing and analytics capabilities on operational performance.

This study makes a valuable contribution to research on sensing and analytics capabilities and DDCs. Our findings also provide researchers and practitioners with important insights into how operational performance can be improved by sensing and analytics capabilities, and the moderating role of a DDC in the relationship between organizational capabilities and operational performance.

Ethics declarations

Conflict of interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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The effects of analytics capability and sensing capability on operations performance: The moderating role of data-driven culture

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Appendix A. Coded articles: Summary of the main studies on the impact of organizational capability on business performance

Study	Code	Type of paper	Sample source/sample size (*N*)	Level of analysis	Dependent variables (DVs)	Independent variables (IVs)	Theory applied	Findings/Contributions
Akter et al. (2016)	**A1**	Empirical research	(1) 2 Delphi studies; (2) Surveys: 152 U.S. business analysts	Organizational	Firm performance	**Independent variables**: big data analytics (BDA) management capability, BDA talent capability, BDA technology capability; **Mediating variable**: BDA capability	Resource-based theory	(1) Value of entanglement conceptualization of a higher-order BDA capability model and its impact on firm performance; (2) moderating effects of analytics capability–business strategy alignment on the relationship between BDAC and business performance.
Ashrafi et al. (2019)	**A2**	Empirical research	Survey: 154 companies with 2 respondents each (CIO/CEO)	Organizational	Firm performance	**Independent variable**: business analytics (BA) capabilities; **Mediating variables**: information quality, firm agility, innovative capability; **Moderating variables**: market turbulence, technological turbulence	Resource-based view	(1) BA capabilities strongly influence a firm's agility through increased innovative capability and information quality; (2) technological and market turbulence moderates the effect of firm agility on firm performance.

Chen and Lin (2021)	**A3**	Empirical research	Survey: 231 middle or senior manager/IT professionals/ chief executives/ CEOs involved in using business intelligence technology in business operations	Organizational	Firm performance	**Independent variable**: sensing capability; **Mediating variables**: transforming capability, driving capability	Dynamic capability theory, organizational evolutionary theory	Strong, positive and cumulative relationships among business intelligence-related dynamic capabilities and structural components of the Sense–Transform–Drive conceptual model can increase firm performance and operating efficiency.
Chi et al. (2010)	**A4**	Empirical research	Secondary data: 12 major automakers (U.S. market) 1988-2003	Organizational	Competitive action: including (1) action heterogeneity, (2) action complexity, (3) action volume	**Independent variable**: network density, structural holes; **Mediating variables**: IT-enabled capability: (a) sensing, (b) responding	Social network theory	IT-enabled capability plays (1) a strengthening role in the relationship between competitive action and network structure for companies embedded in dense network structures and (2) a substitutive role when companies lack advantageous access to brokerage opportunities.
Fosso Wamba et al. (2020)	**A5**	Empirical research	Survey: 202 mid-level executive analytics professionals	Organizational	Organizational outcomes including (1) customer linking capability, (2) financial performance, (3) market performance, (4) strategic business value	**Independent variable**: big data analytics (BDA)-enabled dynamic capability, including BDA-enabled sensing capability; **Mediating variable**: business analytics culture, including analytics culture	Dynamic capabilities view; resource-based view	(1) Analytics culture and BDA-enabled sensing capability positively influence organizational outcomes; (2) an analytics culture mediates the effect of BDA-enabled sensing capability on organizational outcomes.

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Fosso Wamba et al. (2020)	**A6**	Empirical research	Survey: 281 supply chain practitioners in the U.S.	Organizational	Business performance, including (1) costing performance, (2) operational performance	**Independent variables**: big data analytics, environmental dynamism; **Mediating variables**: supply chain ambidexterity, including (1) supply chain agility (2) supply chain adaptability	Dynamic capability view	Big data analytics enhances organizational performance, supply chain adaptability, and supply chain agility, contingent upon the level of environmental dynamism.
Gu et al. (2021)	**A7**	Empirical research	Survey: 108 managers (or above), buyers, purchasing agents in manufacturing and service industries	Organizational	Firm performance	**Independent variable**: supplier development; **Mediating variable**: big data analytics (BDA) capability	Contingency theory, dynamic capability view, resource-based view	A firm's BDA capability has a (1) direct positive impact on firm performance/supplier development and (2) strong mediating/moderating effect on supplier development, affecting business performance improvement.
Hallikas et al. (2021)	**A8**	Empirical research	Survey: 101 managers and experts in manufacturing and service industries	Organizational	Business performance	**Independent variables**: external data analytics capability, internal data analytics capability; **Mediating variables**: digital procurement capability, supply chain performance	Dynamic capability view, resource-based view	(1) There are significant positive relationships between supply chain performance, digital procurement capabilities, and data analytics capabilities; (2) digital procurement capabilities mediate the positive relationship between external data analytics capability and supply chain performance.
Helfat and Peteraf (2015)	**A9**	Conceptual paper	N/A	Organizational	N/A	N/A	N/A	The dynamic managerial capabilities of reconfiguring, seizing, and sensing contribute to differential firm performance under changing conditions.

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Krishnamoorthi and Mathew (2018)	**A10**	Empirical research	Case study: 9 interviews (2014, 2015) with analytics team leaders/senior executives in 2 diverse organizations deploying analytics	Organizational	Business performance	**Independent variables**: analytics resources, including (1) business analytics capability, (2) analytics technology assets; **Moderating variables**: analytics value enhancers, organizational-level variables	Resource-based view	Analytics resources comprising business analytics capabilities and analytics technology assets contribute to firm performance.
Kristoffersen et al. (2021)	**A11**	Empirical research	Survey: 125 top-level managers of firms across Europe	Organizational	Firm performance	**Independent variable**: business analytics capability; **Mediating variables**: resource orchestration capability, circular economy implementation	Theory of resource orchestration	(1) The influence of business analytics capability on firm performance is fully, but not directly, mediated by circular economy implementation and resource orchestration capability; (2) firms with a strong business analytics capability: (a) have a greater ability to excel in a circular economy, (b) increase their resource orchestration capability, (c) build a more sustainable competitive advantage, and (d) have improved firm performance.
Meriton et al. (2020)	**A12**	Review paper	N/A	N/A	N/A	N/A	Dynamic capability view, resource-based view	(1) The generative mechanisms of value in big data technology-enabled supply chains operate at the level of supply chain processes; (2) agility and resilience emerge from big data technology-enabled supply chain management research.
Naseer et al. (2021)	**A13**	Empirical research	Multiple case study: 20 expert interviews with cybersecurity analytics professionals	Organizational	Enterprise cybersecurity performance, including (1) efficiency, (2) effectiveness	**Independent variables**: real-time analytics (RTA) capability, including (1) complex event processing, (2) automated decision-making, (3) on-demand and continuous data	Contingent resource-based view	Firms enable agile characteristics (innovation, flexibility, and swiftness) in IR processes using the characteristics of RTA capability (on-demand and continuous data analysis, decision automation, and complex event processing) to respond to and detect cybersecurity incidents as they occur to

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						analysis; **Mediating variables:** incident response (IR) agility, including (1) flexibility in IR, (2) swiftness in IR, (3) innovation in IR; **Moderating variables:** cyber threat environment, including (1) complexity, (2) dynamism		improve cybersecurity performance.
Ngo et al. (2019)	**A14**	Empirical research	Survey: 150 Vietnamese firms	Organizational	Firm performance	**Independent variables:** technology-sensing capability, market-sensing capability, exploration–exploitation interaction; **Mediating variables:** explorative innovation, exploitative innovation	Dynamic capabilities view	Exploitative and exploratory innovations are salient modi operandi through which the effects of market-sensing and technology-sensing capabilities influence business performance.
Park and Mithas (2020)	**A15**	Empirical research	Fuzzy-set qualitative comparative analysis of 376 organizational level cases in multiple economic sectors during 1999–2006	Organizational	Financial performance, customer performance	**Independent variables:** IT-enabled analytics capability, leadership capability, strategic planning capability, customer focus capability, HR focus capability, process management capability	Complexity theory	IT-enabled information analytics capabilities are critical components of the configurations in which they play multi-faceted roles, varying from enabling to counter-productive to no role in a given context.

Shafiq et al. (2020)	**A16**	Empirical research	Survey: 254 U.S. manufacturers	Organizational	Financial performance	**Independent variable**: Customer pressure for ethical conduct, including (1) code of conduct enforcement; **Mediating variables**: Exsupero-regulatory social practices, including (1) supply chain transparency, (2) employee-focused social practices; **Moderating variables**: supply chain analytics capability	Resource-based view, stakeholder theory	Supply chain analytics capabilities interact synergistically with customer pressure for ethical conduct to improve suppliers' financial and social performance.
Shin et al. (2015)	**A17**	Empirical research	Survey: 244 South Korean SMEs	Organizational	Technology capability, collaborative innovation, organizational learning, internal alignment, firm performance	**Independent variable**: strategic agility; **Mediating variable**: operational responsiveness	N/A	The strategic intent of South Korean SMEs to improve agility positively influences customer retention and operational performance.

Srinivasan and Swink (2017)	A18	Empirical research	Survey: 191 responses from firms in 30 countries (56.8% in the U.S.; 67.5% manufacturing-related and the remainder service-related). The 20 industries included automotive and transportation (8.38%), consumer goods (7.33%), and chemicals (4.19%).	Organizational	Operational performance	**Independent variable**: demand visibility, supply visibility; **Mediating variable**: analytics capability; **Moderating variables**: organizational flexibility	Organizational information processing theory	(1) Supply and demand visibility are associated with the development of analytics capability; (2) analytics capability is associated with operational performance when organizations possess the flexibility to act on analytics-generated insights efficiently and quickly; (3) analytics capability and organizational flexibility are valuable complementary capabilities for firms in volatile markets.
Tallon and Pinsonneault (2011)	A19	Empirical research	Survey: IT and business executives in 241 firms	Organizational	Firm performance	**Independent variable**: strategic IT alignment; **Mediating variable**: firm agility; **Moderating variables**: environmental volatility, IT flexibility	Resource-based view	(1) There are positive/significant links between alignment (can be thought of as sensing capability) and agility and between firm performance and agility; (2) agility fully mediates the effect of alignment on performance; (3) IT infrastructure flexibility moderates the link between agility and alignment in a volatile environment; (4) the influence of IT infrastructure flexibility on agility is as strong as that of alignment on agility; (5) agility and alignment are concurrent and critical organizational goals.

Upadhyay and Kumar (2020)	**A20**	Empirical research	Survey: 800 IT consultants for firms working in big data analytics (India)	Organizational	Firm performance (FP)	**Independent variable**: internal analytics knowledge (KN); **Mediating variables**: big data analytics capability (BDAC), organizational culture (CL)	Dynamic capability view; resource-based view; sociomaterialism theory	(1) CL plays a complementary mediatory role between KN and BDAC that influences FP; (2) BDAC plays a mediatory role between CL and FP.
Vanpoucke et al. (2014)	**A21**	Empirical research	Survey: 719 firms in 20 countries in America, Europe, and Asia	Organizational	Financial performance, integration sensing, integration seizing, integration transforming	**Independent variable**: supplier integrative capability (SIC); **Mediating variables**: market performance, operational performance (process flexibility, cost efficiency)	Dynamic capabilities view; resource-based view; theory of complementarity	(1) Transforming, seizing, and integrating sensing capabilities are complementary, exist simultaneously, enhance cost efficiency/process flexibility and help firms avoid the traditional flexibility/cost tradeoff; (2) market and technological dynamics strengthen the SIC effect on operational performance, but supply base complexity attenuates this link.
Zhu et al. (2021)	**A22**	Empirical research	Modelling: secondary data on big data and analytics implementation 2010–2020	Organizational	Firm performance, including (1) operational efficiency, (2) business growth	**Independent variables**: BDA implementation **Moderating variables**: industry environment, including (1) complexity, (2) dynamism, (3) munificence	Organizational learning theory	(1) BDA implementation significantly affects operational efficiency and business growth; (2) the impact of BDA on operational efficiency is amplified in less complex and dynamic environments; (3) the BDA-business growth relationship is amplified in munificent, complex, and dynamic environments.
This study	**N/A**	Empirical research	Survey: 149 employees of MSMEs in the food industry	Organizational	Operational performance	**Independent variables**: (1) analytics capability, (2) sensing capability **Moderating variables**: data-driven culture	Resource-based view; dynamic capability view; strategic fit theory	(1) Sensing and analytics capabilities positively affect operational performance; (2) a data-driven culture positively moderates the influence of organizational capability on operational performance.

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Appendix B. Papers collected in literature review and major studies

A1. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics*, *182*, 113-131.

A2. Ashrafi, A., Ravasan, A. Z., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management*, *47*, 1-15.

A3. Chen, Y., & Lin, Z. (2021). Business intelligence capabilities and firm performance: A study in China. *International Journal of Information Management*, *57*, 102232, 1-15.

A4. Chi, L., Ravichandran, T., & Andrevski, G. (2010). Information technology, network structure, and competitive action. *Information Systems Research*, *21*(3), 543-570.

A5. Wamba, S. F., Queiroz, M. M., Wu, L., & Sivarajah, U. (2020). Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture. *Annals of Operations Research*, 1-20

A6. Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*, 107498. 1-14.

A7. Gu, V. C., Zhou, B., Cao, Q., & Adams, J. (2021). Exploring the relationship between supplier development, big data analytics capability, and firm performance. *Annals of Operations Research*, 1-22.

A8. Hallikas, J., Immonen, M., & Brax, S. (2021). Digitalizing procurement: the impact of data analytics on supply chain performance. *Supply Chain Management: An International Journal*, 26(5), 629–646.

A9. C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal*, *36*(6), 831-850.

A10. Krishnamoorthi, S., & Mathew, S. K. (2018). Business analytics and business value: A comparative case study. *Information & Management*, *55*(5), 643-666.

A11. Kristoffersen, E., Mikalef, P., Blomsma, F., & Li, J. (2021). The Effects of Business Analytics Capability on Circular Economy Implementation, Resource Orchestration, Capability and Firm Performance. *International Journal of Production Economics*, 108205, 1-19.

A12. Meriton, R., Bhandal, R., Graham, G., & Brown, A. (2020). An examination of the generative mechanisms of value in big data-enabled supply chain management research. *International Journal of Production Research*, 1-28.

A13. Naseer, A., Naseer, H., Ahmad, A., Maynard, S. B., & Siddiqui, A. M. (2021). Real-time analytics, incident response process agility and enterprise cybersecurity performance: A contingent resource-based analysis. *International Journal of Information Management*, *59*, 102334.1-10.

A14. Ngo, L. V., Bucic, T., Sinha, A., & Lu, V. N. (2019). Effective sense-and-respond strategies: Mediating roles of exploratory and exploitative innovation. *Journal of Business Research*, *94*, 154-161.

A15. Park, Y., & Mithas, S. (2020). Organized Complexity of Digital Business Strategy: A Configurational Perspective. *MIS Quarterly*, *44*(1), 85-127.

A16. Shafiq, A., Ahmed, M. U., & Mahmoodi, F. (2020). Impact of supply chain analytics and customer pressure for ethical conduct on socially responsible practices and performance: An exploratory study. *International Journal of Production Economics*, *225*, 107571, 1-12.

A17. Shin, H., Lee, J. N., Kim, D., & Rhim, H. (2015). Strategic agility of Korean small and medium enterprises and its influence on operational and firm performance. *International Journal of Production Economics*, *168*, 181-196.

A18. Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, *27*(10), 1849-1867.

A19. Tallon, P. P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model. *MIS Quarterly*, 463-486.

A20. Upadhyay, P., & Kumar, A. (2020). The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *International Journal of Information Management*, *52*, 102100. 1-16.

A21. Vanpoucke, E., Vereecke, A., & Wetzels, M. (2014). Developing supplier integration capabilities for sustainable competitive advantage: A dynamic capabilities approach. *Journal of Operations Management*, *32*(7-8), 446-461.

A22. Zhu, S., Dong, T., & Luo, X. R. (2021). A longitudinal study of the actual value of big data and analytics: The role of industry environment. *International Journal of Information Management*, *60*, 102389, 1-15.

Appendix C - Profile of the respondents (n = 149)

Demographic	Category	n = 149	%
Gender	Men	86	58
	Women	63	42
Age group (years)	21–25	20	13
	26–30	56	38
	31–35	45	30
	36–40	22	15
	41–45	4	3
	45–50	2	1
Education level	Secondary	6	4
	Diploma	20	13
	Associate degree	4	3
	Bachelor's degree	102	68
	Master's degree	12	8
	Doctorate or above	4	3
Occupation	CEO	2	1
	CFO	1	1
	Supply chain manager	24	16
	R&D manager	7	5
	Product development manager	16	11
	Merchandising manager	10	7
	Production manager	15	10
	Logistics (or shipping) manager	21	14
	Sales/marketing manager	12	8
	Food safety manager	13	8
	Quality assurance manager	10	7
	Owner	18	12
Engaged in food industry (Years)	5–10	111	74
	11–20	37	25
	21 or above	1	1
Engaged in current position (Years)	5–10	127	85
	11–20	21	14
	21 or above	1	1
Number of employees in current company	1–9	29	19
	10–49	43	29
	50–249	77	52
Age of company (Years)	5–10	45	30
	11–20	79	53
	21 or above	25	17
Type of company	Food producer	36	24
	Food processor	30	20

Wholesaler	25	17
Retailer	30	20
Restaurant	28	19

Appendix D - Scale items

A seven-point Likert scale was used for all the items (1 = "strongly disagree"; 4 = "neutral"; 7 = "strongly agree")

Analytics Capability (Srinivasan and Swink, 2018)
Please tell us the degree to which data management and analysis techniques are used to improve supply chain strategies and activities:
AC1: We use advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making.
AC2: We easily combine and integrate information from many data sources for use in our decision making.
AC3: We routinely use data visualization techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information.
AC4: Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement.
AC5: We deploy dashboard applications/information to our managers' communication devices (e.g., smart phones, computers).

Sensing capability (Pavlou and El Sawy, 2011)
SC1: We frequently scan the environment to identify new business opportunities.
SC2: We periodically review the likely effect of changes in our business environment on customers.
SC3: We often review our product development efforts to ensure they are in line with what the customers want.
SC4: We devote a lot of time implementing ideas for new products and improving our existing products.

Data-driven culture (Zhang et al., 2020)
DDC1: We consider data a tangible asset.
DDC2: We base our decisions on data rather than on instinct.
DDC3: We are willing to override our own intuition when data contradict our viewpoints.
DDC4: We continuously coach our employees to make decisions based on data.

Operational performance (Wang et al., 2012)
Over the past three years, we have performed better than our key competitors in
OP1. Decreasing product/service delivery cycle time.
OP2. Rapidly responding to market demand changes.
OP3. Rapidly bringing new products/services to the market.
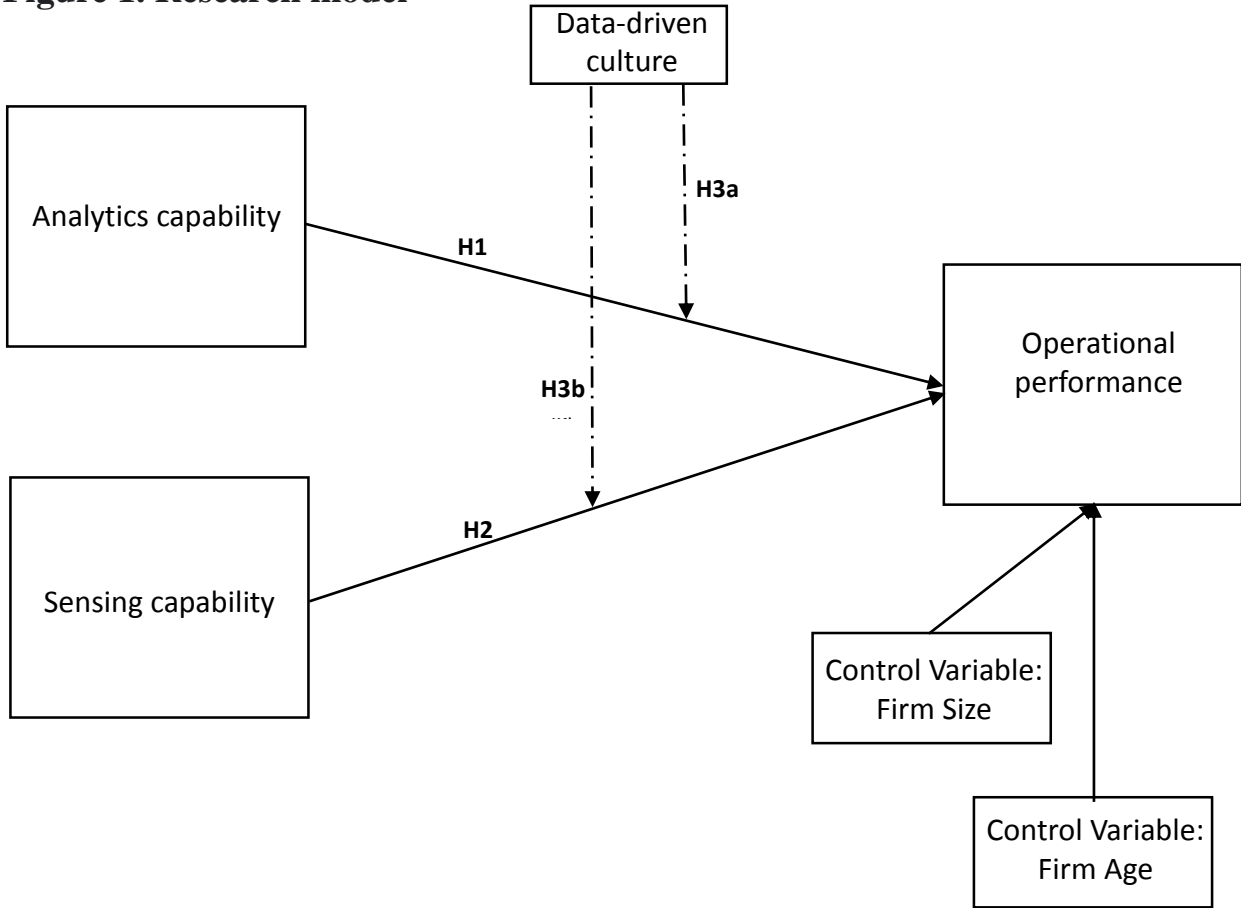OP4. Rapidly entering new markets.
OP5. Rapidly confirming customer orders.
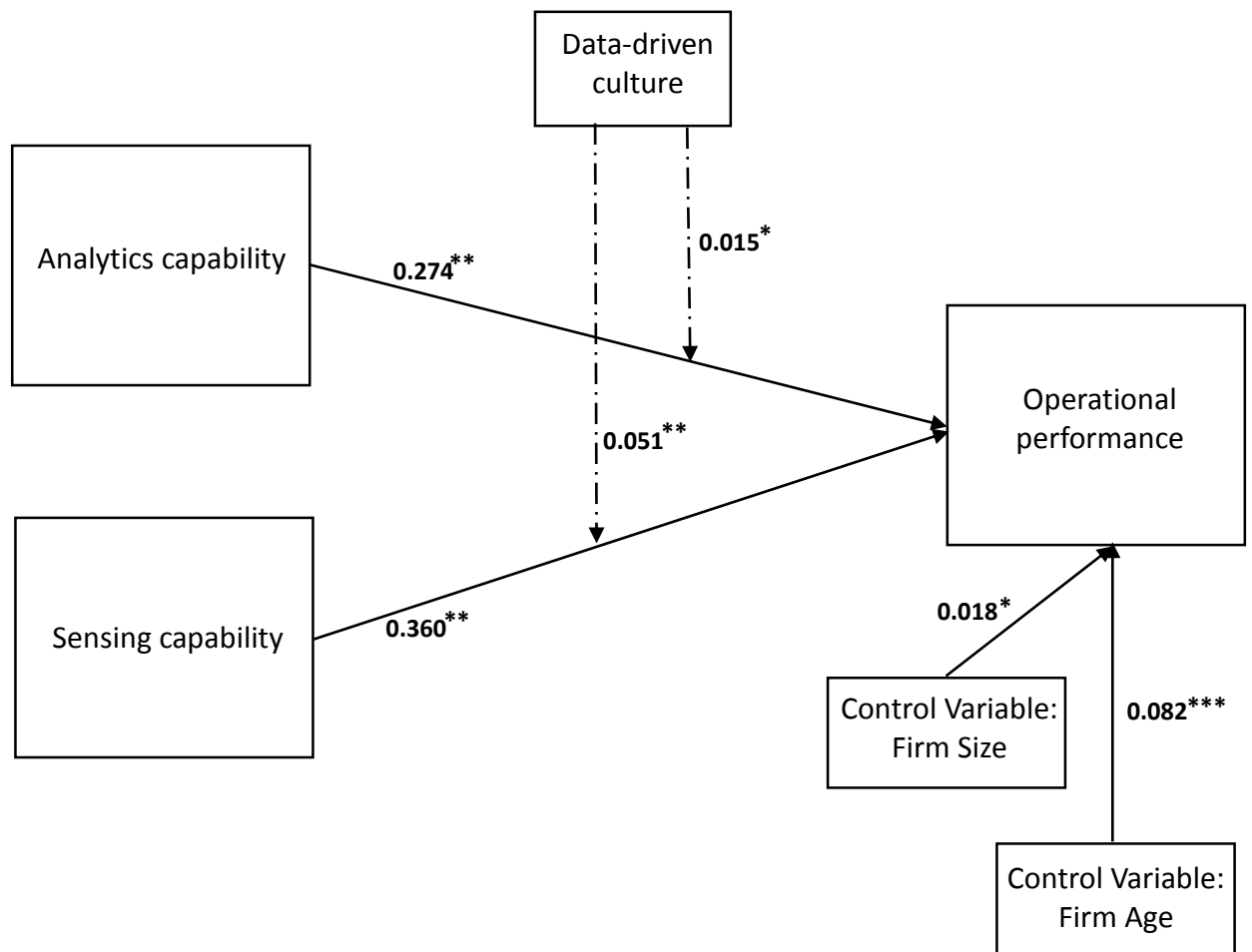OP6. Rapidly handling customer complaints.
OP7. Establishing a strong and continuous bond with customers.

Figures

Figure 1. Research model

Figure 2. Data analysis results in the study

Note: ***p<0.01, **p<0.05, *p<0.1.

Table

Tables

Table 1. Loading of the indicator variables (Sample size = 149)

Construct	Items	Loadings	Mean	Standard deviation	Significant level
Operational Performance	OP1	0.66	5.91	1.17	$p<0.05$
	OP2	0.72	5.70	1.08	$p<0.05$
	OP3	0.71	5.61	1.29	$p<0.05$
	OP4	0.74	5.50	1.20	$p<0.05$
	OP5	0.75	5.72	1.24	$p<0.05$
	OP6	0.65	5.85	1.23	$p<0.05$
	OP7	0.69	6.01	1.12	$p<0.05$
Analytics Capability	AC1	0.70	5.44	1.24	$p<0.05$
	AC2	0.66	5.52	1.14	$p<0.05$
	AC3	0.68	5.62	1.08	$p<0.05$
	AC4	0.72	5.55	1.13	$p<0.05$
	AC5	0.75	5.54	1.24	$p<0.05$
Sensing Capability	SC1	0.79	5.72	1.13	$p<0.05$
	SC2	0.73	5.56	1.31	$p<0.05$
	SC3	0.77	5.79	1.1	$p<0.05$
	SC4	0.63	5.60	1.20	$p<0.05$
Data-driven Culture	DC1	0.74	5.66	1.09	$p<0.05$
	DC2	0.74	5.79	1.05	$p<0.05$
	DC3	0.64	5.64	1.11	$p<0.05$
	DC4	0.66	5.70	1.16	$p<0.05$

Table 2. Inter-construct correlation

Items	Operational Performance	Analytics Capability	Sensing Capability	Data-driven Culture	Firm Size	Firm Age
OP1	0.66	0.32	0.36	0.26	-0.05	0.08
OP2	0.72	0.33	0.45	0.28	-0.04	0.04
OP3	0.71	0.39	0.40	0.39	-0.06	0.03
OP4	0.74	0.47	0.49	0.28	-0.01	-0.11
OP5	0.75	0.37	0.42	0.29	0.05	-0.15
OP6	0.65	0.50	0.45	0.43	-0.04	-0.20
OP7	0.69	0.50	0.45	0.39	0.04	0.001
AC1	0.44	0.70	0.54	0.37	0.23	0.21
AC2	0.32	0.66	0.44	0.55	-0.01	-0.01
AC3	0.37	0.68	0.45	0.43	-0.02	0.11
AC4	0.48	0.72	0.50	0.34	-0.03	-0.13
AC5	0.45	0.75	0.48	0.41	0.07	0.03
SC1	0.48	0.51	0.79	0.41	-0.01	-0.08
SC2	0.54	0.51	0.73	0.31	0.03	-0.02
SC3	0.43	0.53	0.77	0.42	-0.02	-0.11
SC4	0.32	0.49	0.63	0.36	0.09	0.03
DC1	0.38	0.47	0.45	0.74	-0.06	0.01
DC2	0.38	0.40	0.33	0.74	-0.01	0.05
DC3	0.23	0.29	0.28	0.64	-0.10	0.05
DC4	0.30	0.44	0.31	0.66	0.02	0.18
FS	0.02	0.07	0.02	-0.05	1.00	0.24
FA	0.08	0.06	-0.07	0.10	0.24	1.00

*Item legend: OP: Operational performance; AC: Analytics capability; SC: Sensing capability; DC: Data-driven culture; FS: Firm size; FA: Firm age

Table 3. Descriptive statistics and correlation matrix of full sample

Constructs	Cronbach's Alpha	Composite Reliability	Analytics Capability	Data-driven Culture	Firm Age	Firm Size	Operational Performance	Sensing Capability
Analytics Capability	0.743	0.828	0.701					
Data-driven Culture	0.644	0.787	0.582	0.694				
Firm Age	1.000	1.000	0.056	0.096	1.000			
Firm Size	1.000	1.000	0.071	-0.049	0.236	1.000		
Operational Performance	0.824	0.870	0.595	0.476	-0.079	-0.019	0.703	
Sensing Capability	0.713	0.821	0.691	0.501	-0.070	0.023	0.616	0.732

*Remark: Bold diagonals represent the square root of average variance extracted (AVE) for multi-item scale.