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From Aspirational to Transformed: Configurational Recipes for Analytics-Driven Operational Excellence

Dr. Liangliang Hua

Southeast University, China
Email: 101012981@seu.edu.cn

Dr. Di Mao

School of Business, Operation and Strategy
University of Greenwich, United Kingdom
Email: d.mao@greenwich.ac.uk

Prof. Rekha Rao-Nicholson

Essex Business School
University of Essex, United Kingdom
Email: rekha.raonicholson@essex.ac.uk

Dr. Chia-Hui Yu*

National Taipei University of Business, Taiwan, (R.O.C.)
Email: crystal.yu@ntub.edu.tw

Prof. Huimin Lu

Southeast University, China
Email: luhuimin@ericlab.org

Dr. Yichuan Wang

Sheffield University Management School
University of Sheffield, United Kingdom
Email: yichuan.wang@sheffield.ac.uk

* Corresponding author

ABSTRACT

Analytics technologies are critical for optimizing operational performance, yet the effective configurations for leveraging these technologies remain underexplored. Grounded in complexity theory and contingency theory, this paper elucidates how supply chain governance, organizational capability, and environmental conditions interact with varying levels of analytics capability to enhance operational performance. Using secondary data from 205 Chinese high-tech enterprises over two years, we conduct a rigorous content analysis and employ fuzzy-set qualitative comparative analysis (fsQCA) to identify the configurations that drive operational performance. Our findings reveal that firms must tailor their organizational capabilities, supply chain governance, and environmental strategies according to their specific level of analytics capability, categorized as aspirational, experienced, and transformed, to achieve optimal performance. This study enriches the digital technologies stream of operation and supply chain management literature by offering a novel approach to understanding the complex dynamics of analytics technology implementation and providing actionable insights for managers.

Keywords: Operational performance; Analytics technology; Supply chain governance, complexity theory, fuzzy-set qualitative comparative analysis (fsQCA)

1. INTRODUCTION

While conventional wisdom suggests that investments in Information Technology (IT) lead to enhanced organisational performance, the appropriate scale of investment in digital technologies remains debated (Mahmood et al., 2000; Mithas & Rust, 2016). Analytics-enabled technologies, for instance, are pivotal in optimising operations and transforming business models, as highlighted by significant investments by high-tech organizations (Kache and Seuring, 2017; Müller *et al.*, 2018; Xia et al., 2024) and service organizations (Khanra et al., 2020). For example, the e-commerce giant Taobao leverages large stream data-mining techniques to analyse visitor browsing data, optimising pricing, predicting customer demand, and ultimately, enhancing decision-making efficiency. These technologies have proven

effective in boosting productivity (Müller et al., 2018), reducing operational risks and costs (Hossain et al., 2023), and managing inventory efficiently (Huang and Van Mieghem, 2014; Wong & Ngai, 2023).

However, despite these advantages, the majority of analytics projects fail (Asay, 2017; Henrion, 2019). A critical factor contributing to this high failure rate is the lack of collaboration with supply chain partners, identified in Kache and Seuring's (2017) Delphi study as a significant impediment to reaping the benefits of analytics-enabled technologies. Although there is substantial research on the impact of analytics-enabled technologies on organisational performance focusing on internal environmental factors—such as changes in business processes, strategies, and routines (e.g., Srinivasan and Swink, 2018)—the influence of external exogenous contexts such as supply chain governance (SCG) and operating environments on the implementation of analytics-enabled technologies is less understood (Chen *et al.*, 2014; Müller *et al.*, 2018).

Drawing on previous research in the information systems domain (Melville *et al.*, 2004) and complexity theory (El Sawy *et al.*, 2010; Park and Mithas, 2020), we propose that successful analytics-based technologies implementation requires optimal combinations of several elements. These elements include robust analytics capability, a firm's ability to absorb knowledge, and the capacity to leverage supply chain environments, including supplier and customer concentration, diversification, and environmental conditions. This argument is evident in the findings of Melville *et al.* (2004) that the organisational factors, characteristics of supply chain partners, and industrial environments are crucial to achieving information technology (IT) business value generation. In the same vein, Pavlou and El Sawy (2010) suggest that firms' IT capability is significantly influenced by their business environments. A good fit between new technology and dominant forces in the business environment is necessary for creating sustained organisational performance (Xue *et al.*, 2012).

Furthermore, not many companies can rival Taobao in terms of the scale of analytics-enabled technologies investment. In practice, most organisations struggle to progress in their analytics initiatives due to the high costs and risks associated with such systems (Vidgen *et al.*, 2017). For instance, maintaining a Hadoop system is estimated to cost approximately \$9.3 million over five years (Winter *et al.*, 2013). Consequently, firms with budget constraints may end up with limited analytics capabilities. This observation leads to an intriguing research question: *How can firms with varying levels of analytics capability optimise their operational performance?*

While recent advancements in artificial intelligence, robotics, and business process management (BPM) automation have generated significant insights into the design and ethical use of intelligent systems, our study takes a distinct focus to address this research question. Rather than addressing the normative or algorithmic dimensions of AI, we examine the strategic orchestration of analytics capability, that is, how firms align organizational resources, governance structures, and environmental conditions to achieve operational excellence. This approach offers conceptual novelty by integrating complexity theory and contingency theory within a configurational framework (fsQCA), thereby revealing multiple, equifinal pathways to superior performance. Practically, our findings extend beyond process automation or system ethics by providing a diagnostic model and decision matrix that guide managers in deploying analytics capabilities effectively across different maturity stages. This positioning underscores our study's contribution to the analytics-driven operations and supply chain management literature, rather than to the robotics or AI ethics domains.

2. THEORETICAL BACKGROUND

2.1. Complexity of analytics technology implementation

The existing empirical research has often focused on examining the direct effects of analytics on outcomes of interest (Oesterreich et al., 2022; Wang et al., 2018) or, at best, investigating the moderating role in the analytics-organisational performance linkages (e.g., Srinivasan and Swink, 2018; Müller *et al.*, 2018). Achieving successful analytics technology implementation requires a shift from merely focusing on analytics per se to disentangling complex intersections between analytics and other organisational elements. In practice, the analytics is an enormously complex system, and its implementation requires dramatic changes in operations and business processes (Wang *et al.*, 2019) or even business model (Kanungo et al., 2024). For example, organisations need to develop new data-centric approaches to collaborate with their supply chain partners in order to thoroughly collect and process consumer data. However, the complexity of analytics technology implementation has not been well studied. We lack studies that explore what parsimonious configurations are for leveraging analytics to facilitate operational performance.

Complexity theory has viewed complexity as a “*structural variable that characterises both organisations and their environments*” (Anderson, 1999, p. 216). Complexity exists because several subsystems operate in parallel within the organisation. Research has found that complexity increases the possibility of IT implementation failure (Xin and Choudhary, 2019). The reasons for IT implementation failure could be related to organisational, technical, and social, and industrial environment issues. One major cause is that IT capabilities embedded in an IT system are misfit with organisational structure, business process, and environment (Strong and Volkoff, 2010). To mitigate such misfits, organisations have been suggested to find optimal configurations emergent from complex interactions among multiple elements existing in social and technical systems of organisations (Zammuto *et al.*, 2007). Thus, complexity theory provides an excellent anchor to explain how multiple elements interact with one another in a non-linear way to produce desired outcomes (Park and Mithas, 2020).

2.2. Defining analytics capability

In this study, we adopt LaValle *et al.*'s (2011) definition of analytics capability, which is defined as three distinct capability levels: aspirational, experienced, and transformed. analytics capability is classified based on the motive for adoption, functional proficiency, data management, and analytics in action. The *aspirational analytics* organisations have a limited ability to capture, integrate and analyse data to acquire more profound business insights, due to a lack of data governance and information sharing culture. The *experience analytics* organisations have analytical experience along with better data governance and information sharing culture and thus have the potential to achieve cost reduction and operation optimisation. The *transformed analytics* organisations mainly use predictive and prescribe analytics to guide strategic actions. Such a classification of analytics capability could be a useful approach to assess the organisation's analytics capability and implementation and identify whether better uses of analytics have transformed organisations.

Although prior research has developed a rich understanding of the role of analytics in improving organisational performance (Chatterjee *et al.*, 2024; Gopal *et al.*, 2024; Pathak *et al.*, 2023), the question of how firms with different level of analytics capability can orchestrate their internal and external resources to optimise operational performance remains unsolved. According to contingency theory, superior performance of a firm depends on the extent to which its internal features (e.g., adoption of the best practices or technology) can match the situational demands of its external environments (Roh *et al.*, 2016). In fact, analytics does not ubiquitously apply to all external exogenous contexts. firms with different levels of analytics capability should have different business strategies or organisational capability to complement their analytics initiatives. Therefore, this study treats analytics capability as a contingency condition in configurations. By doing so, this enables organisations who are at the different

stage of analytics deployment to understand what the ideal configurational solutions are for achieving high performance.

2.3. Configurational approach to studying analytics technology implementation

By combining the perspectives of complexity theory and contingency theory, we propose a theoretical model as shown in Figure 1 to comprehensively capture the interplay between contingency conditions (i.e., analytics capability) and configurational elements. Specifically, we examine how the SCG, organisational capability, and environmental condition interact with different levels of analytics capability to achieve superior operational performance. We next provide a brief review of three feasible elements that might be able to configure with analytics capability to achieve higher level of operational performance.

First, knowledge absorptive capacity can be viewed as a higher-order organisational capability (Liu *et al.*, 2013; Roberts *et al.*, 2012) that enables firms to identify, assimilate and exploit lower-order capabilities (e.g. IT capability and operational capability) to help organisations acquire and sustain a competitive advantage (Grewal and Slotegraaf, 2007). Prior research (e.g., Pavlou and El Sawy 2010; Roberts *et al.*, 2012) suggests that knowledge absorptive capacity can complement IT capability in creating business value. With this mind, we argue that obtaining capabilities from the use of analytics technology to increase operational performance cannot be guaranteed unless organisations have sufficient capacity to identify, absorb, transform and exploit the knowledge that is generated from analytics. Thus, knowledge absorptive capacity is chosen as one of the configurational elements that complements other external conditions to produce an optimal operational performance in analytics technology implementation.

Second, supply chain management literature claims that the survival of a firm depends upon its ability to manage relationships with suppliers, customers, or other organisations in the

supply chain (Mahapatra *et al.*, 2019; Shu and Lewin, 2017). Wang *et al.* (2020) argue, inappropriate governance of the supply chain may disrupt firms' analytics deployment. For instance, diversity of supply chain data across various business partners may hinder its integration into a firm's processes, while the volume and velocity of supply chain data may further complicate the early deployment of analytics, especially for those associated with highly specialised algorithms (Moe and Schweidel, 2017). Thus, SCG plays a pivotal role in implementing analytics technologies. For clarity, we refer to this construct as SCG rather than a broader term such as "operational governance," because SCG specifically denotes the governance of supplier–customer relationships, encompassing both formal contractual controls and informal relational mechanisms. SCG focuses on (1) relational governance (Zaheer and Venkatraman, 1995), and (2) contractual governance (Poppo and Zenger, 2002). Relational governance is defined as "*the structure and the process of an interorganisational relationship*" (Zaheer and Venkatraman, 1995, p. 374), while contractual governance refers to any formal promises or obligations agreed by supply chain partners to ensure the quality in the production process (product) and strengthen buying and selling (market) relationship (Poppo and Zenger, 2002). Drawing on resource dependence theory, we select the concentration of supply chain partners (i.e., supplier concentration and customer concentration) and diversification of product and market (i.e., product diversity and market diversity) to capture the relational and contractual aspects of SCG respectively.

Supplier concentration (SC) refers to the portion of a focal firm's sales purchasing spend that goes to its primary suppliers (Schwieterman *et al.*, 2018). A complex supply chain network may involve a large number of suppliers, which in turn may lead to "upstream complexity" issues in the supply chain (Steven *et al.* 2014). On the other hand, having a more concentrated supply base enables a company to achieve superior financial performance (Lanier Jr *et al.*, 2010). Customer concentration (CC) refers to the extent to which companies depend on their

key customers. High CC indicates that the revenues of a company are concentrated across a small group of customers (Saboo *et al.* 2017). On the other hand, low CC refers to a situation in which each customer can only contribute to a small proportion of revenue. Although the existing research has linked supply-based and customer-based concentration to various aspects of organisational performance, to the best of our knowledge, no study has linked the concept of supply chain concentration to the analytics technology implementation.

Product diversity refers to the extent to which the diversity of the product/service a company offering to the market (Chen *et al.*, 2009a). In this research, we also investigate another diversification strategy from a geographical angle - Market diversity. It relates to the “*breath of a firm’s customers and markets*” (Gnyawali *et al.*, 2006, p. 515). More specifically, we define the market diversity as the number of regional markets that a company is selling its products. There is a long tradition of discussing the diversification strategy in the management literature as it sheds important light on how the company can ensure the efficiency in utilising various resources (Tallman and Li, 1996). The advantages of diversification are associated with the economies of scope (Tallman and Li, 1996). That is, the company can be benefited from the sharing resources across different products and markets while satisfying wider customers’ demands (Zahavi and Lavie, 2013). However, diversification is also critiqued by its inherent risks that might lead to substantial costs. For example, from the perspective of transaction cost theory, offering diverse product range beyond a certain degree will result in higher internal governance costs and harm the firm’s performance (Jones and Hill, 1988).

Third, we propose firms’ industrial environments can be considered as one of the elements in configurations. Environmental munificence and environmental stability are selected to capture firms’ industrial environment. Environmental munificence refers to the critical demands, opportunities, and resources for firms’ growth within a business environment (Castrogiovanni, 1991). Firms find it relatively easy to achieve and sustain growth when resources are abundant

in the business environment; however, when resources are scarce, it is difficult for firms to survive. Indeed, the deployment of analytics technologies is inherently linked to the exploration of opportunities, satisfaction of demand, and utilisation of resources within a business environment (Park *et al.*, 2017). It has been found that, in an environment of high munificence, firms are more likely to devote greater analytical effort to explore new business opportunities and overcome market threats. Kitchens *et al.* (2018) suggest that analytical capability can be improved in high-volume data environments because analytics requires substantial resources from customers (e.g., purchase histories, transactional data, and behavioural data) to make an accurate analysis, and mature analytical processes to achieve superior performance (Wang *et al.*, 2018). Hence, firms that gain various resources for innovation and competition in the market could benefit more from analytics than those firms located in poor resource environments, since there would be more demand for, and more opportunities to support, the use of analytics.

Environmental stability refers to a situation of predictable change or variability in a business environment (Sitkin *et al.*, 1994). Many firms continue to struggle to gain the benefits from their investments in analytics, since realising the vast potential of analytics requires firms to undergo organisational and environmental adjustments. In highly unpredictable business environments, firms will find it difficult to interpret the unpredictable events effectively, even with the use of business analytics (Park *et al.*, 2017). In contrast, when instability in the business environment is low, firms are better able to explore the opportunity to improve their operations and have more time to devote to the deployment of analytics. In line with this, we posit that the functionalities that analytics technologies provide are more effective in supporting firms to improve operational efficiency when the business environment is stable.

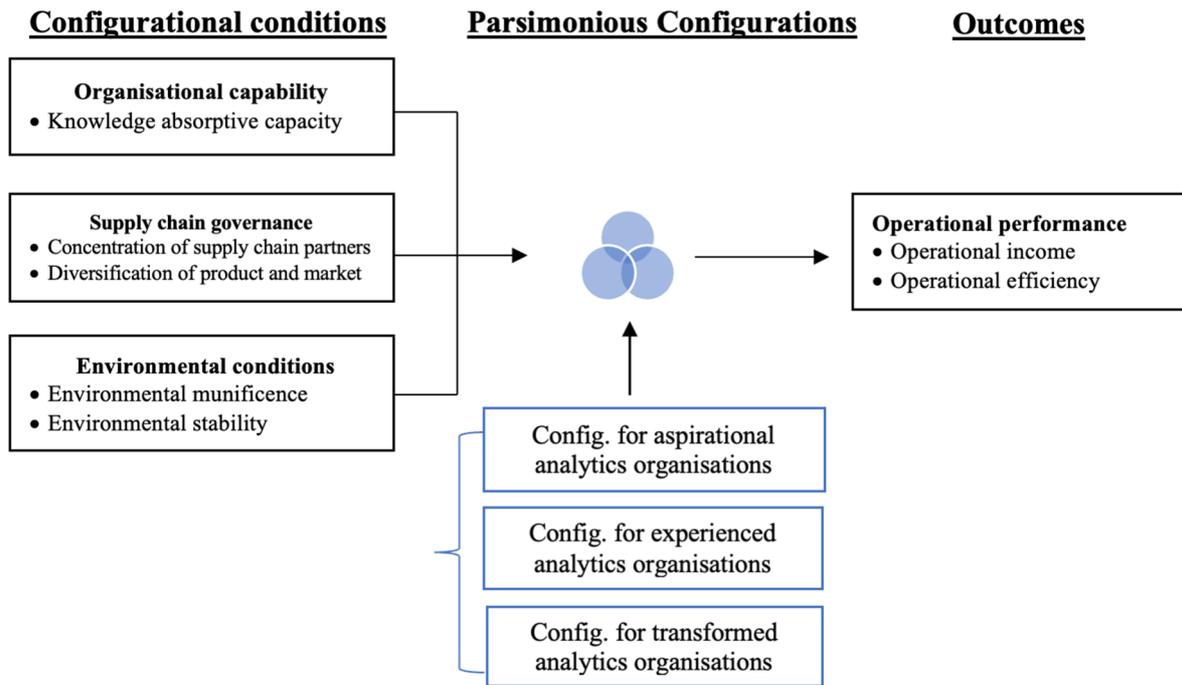


Figure 1. Nomological network of configurations producing operational performance under different level of analytics capability

3. RESEARCH METHODS

3.1. Empirical setting and data collection

The sample we selected was driven by the constructs determined in the theory discussion above as well as the availability of the data needed to measure the variables. The period of observation is from 2015 to 2016. The dataset was constructed using 692 Chinese high-tech companies covering the period 2015 to 2016. We have justified for selecting the 2015–2016 window by emphasizing two key reasons: (1) this period captures a major phase of analytics adoption among Chinese high-tech firms, following the government’s Made in China 2025 initiative (State Council of the People’s Republic of China, 2015), which stimulated widespread investment in data-driven operations; and (2) reliable and consistent disclosure of analytics-related practices became available during this time, allowing systematic content analysis across firms.

The High Technology (Manufacturing) Classification Standard established by the National Bureau of Statistics of the People's Republic of China (2013) was adopted for this study. According to this classification, the companies from the pharmaceutical industry, aircraft and spacecraft manufacturing, electric machinery and equipment manufacturing, manufacturing of computers and communications, and special-purpose equipment manufacturing were included in this study. Of the 692 firms, there was no data on operational efficiency for 202 firms, and also 141 had missing data with regard to their major supplier or major customer information. Lastly, we had a few missing observations for R&D data, leaving 327 firms in our sample. Out of these 327 firms, we observed that 122 firms had no notable capability in analytics; hence, we removed these firms from our sample. The final sample consists of 205 firms. To reflect the causal relationship, this research considered a one-year lag between the dependent variable and the independent variable. Given that the operational efficiency was measured by the companies' data for 2016, we collected the data related to analytics capability and all proposed conditions for 2015. Figure 2 shows the flow chart of the empirical setting.

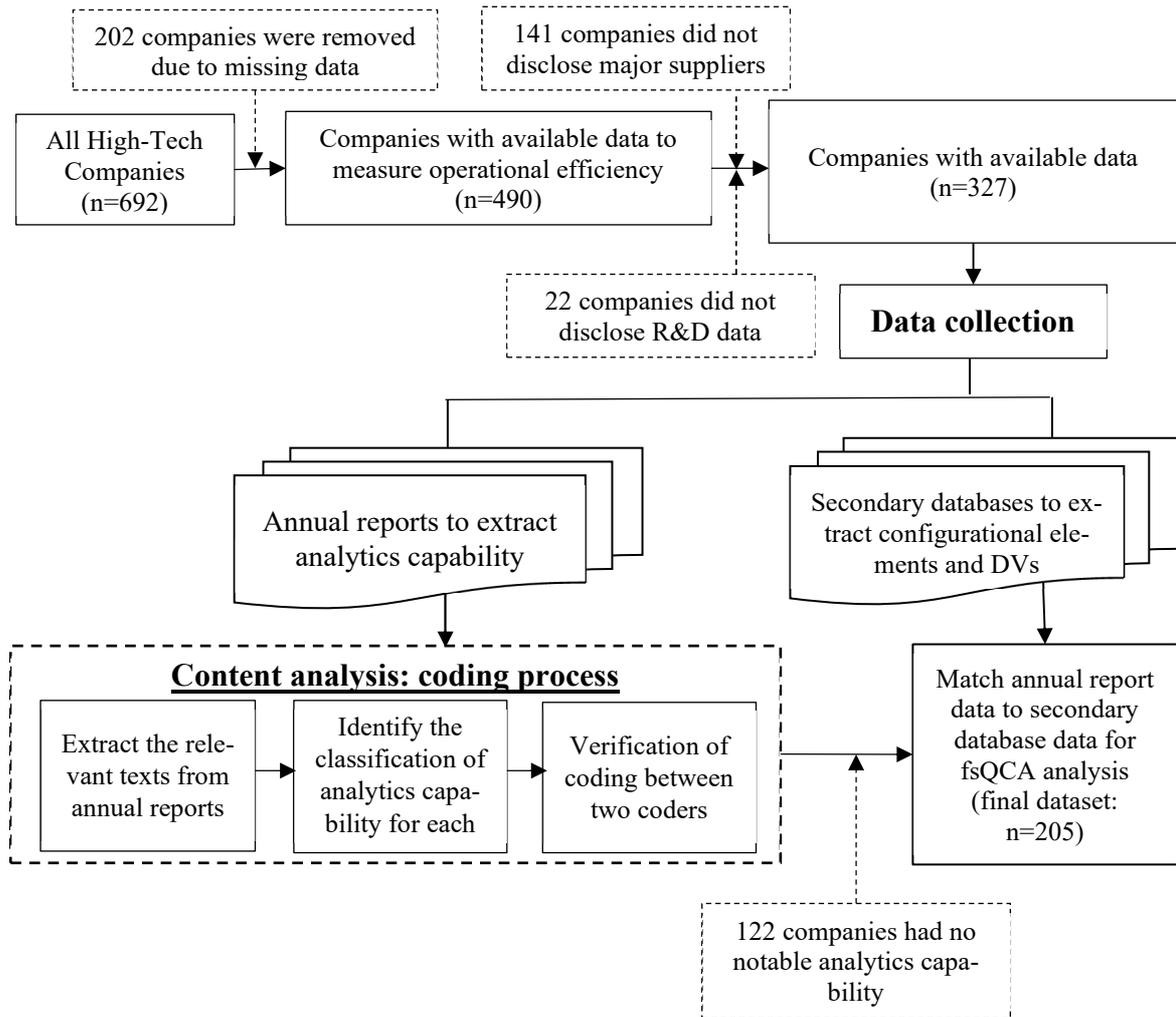


Figure 2. Flow chart of empirical setting

3.2. Construct Operationalisation

3.2.1. Dependent variable – operational performance

We measure operational performance using *operational income* directly obtained from the China Stock Market and Accounting Research database (CSMAR) and operational efficiency. We measured operational efficiency by the Stochastic Frontier Estimation (SFE) methodology (Lam *et al.*, 2016). A key advantage of adopting SFE is that it can be used to measure the firm's relative efficiency in its industry. The SFE method explicitly incorporates the random error term into its estimation and can, therefore, capture more accurately the variations in efficiency (Vandaie and Zaheer, 2014). We computed the operational efficiency

through two operational functions: *operational output* and *operational input*. Regarding the output function, we observed the firm's operating income, which can be regarded as an outcome of a firm's ongoing operations (Hendricks and Singhal, 2005). Following Li *et al.* (2010), three variables were adopted to measure the operational input, namely, labour, capital, and COGS. Labour can be measured by the number of employees (Lam *et al.*, 2016). COGS refers to the costs of providing customers with products or services. Li *et al.* (2010) argue that to be operationally efficient, a company needs to invest in productivity-enhancing processes and tools. To capture such investment, we collected the data on companies' capital expenditures. After collecting all the information as mentioned above, we used *Frontier (4.1)* to construct a stochastic production function to implement the SFE, as follows:

$$(1) \quad \ln(\text{Operating Income})_{ijt} \\ = \beta_0 + \beta_1 \ln(\text{Number of Employees})_{ijt} + \beta_2 \ln(\text{Cost of Goods Solds})_{ijt} \\ + \beta_3 \ln(\text{Capital Expenditure})_{ijt} + \varepsilon_{ijt} - \eta_{ijt}$$

where for company i from industry j ($t=2016$), the stochastic random error is represented by ε_{ij} and *technical inefficiency* is represented by η_{ij} . The purposes of the stochastic production function are to estimate technical inefficiency and to calculate the operational efficiency. Regarding technical inefficiency η_{ij} , the value ranges from 0 to 1. For example, if a company has a technical inefficiency of 0, it will be regarded as having no technical inefficiency (i.e., it is extremely efficient). According to Lam *et al.* (2016), technical inefficiency is a relative measure of how inefficient a firm is when compared with the frontier in the corresponding industry. To calculate the operational efficiency, we followed Lam *et al.* (2016) to transform η_{ij} as follows:

$$(2) \quad \text{Operational Efficiency}_{ijt} = 1 - \widehat{\eta}_{ijt}$$

3.2.2. Configurational elements

Supplier Concentration. SC measures the extent to which a company's suppliers are concentrated (Steven *et al.*, 2014). The SC data were manually collected from companies' annual reports. Following Kim (2017), SC was measured by the *Herfindahl-Hirschman (HH) index*. The data collected from the annual reports in the section that covers the Major Supplier Situation reveal the money flow between companies and suppliers on a cost basis. The value of SC also ranges from 0 to 1; the higher value of this measure indicates that a company's suppliers are concentrated.

$$(3) \quad \text{Supplier Concentration}_i = \sum_{j=1}^N \left(\frac{\text{Purchasing Cost}_{ij}}{\text{COGS}_i} \right)^2$$

where $\text{Purchasing Cost}_{ij}$ is the direct cost to company i associated with the activities of purchasing from supplier j and COGS_i is the cost of goods sold by company i in 2015.

Customer Concentration. To measure the CC, we followed Saboo *et al.* (2017) to adopt the sum of the square of revenue share from major customers. According to the *Standards for the Contents and Formats of Information Disclosure by Companies Offering Securities to the Public No.3*, the listed companies in China are required to disclose their top five major customers, with the information of revenue contributions. Given that the existing data vendors do not provide this information, the data used for calculating the CC were also manually collected from the companies' annual reports. In line with the existing research (Saboo *et al.*, 2017), we measure CC as in equation (4):

$$(4) \quad \text{Customer Concentration}_i = \sum_{j=1}^N \left(\frac{\text{Sales}_{ij}}{\text{Sales}_i} \right)^2$$

where $Sales_{ij}$ is the sales revenue of firm i from customer j and $Sales_i$ is the total sales of firm i . Hence, the value of a firm's CC also ranges from 0 to 1, where 0 indicates that a firm's revenues are evenly distributed across its customers, and 1 indicates that all revenues of a firm are obtained from a single customer (Saboo *et al.*, 2017).

Knowledge absorptive capacity. While there is no absolute measure consistently used in the existing research (Chen *et al.*, 2009b), it is widely acknowledged that knowledge absorptive capacity is building on the basis of the organisational knowledge and ability after a series of R&D activities (Tseng *et al.*, 2011). Therefore, we measure the knowledge absorptive capacity through firms' R&D activities from both input and output perspectives. That is, the more R&D input (proxied by R&D expenses) and more R&D outputs (proxied by number of patents received), the company ought to be associated with stronger knowledge absorptive capacity. To create the variable of knowledge absorptive capacity, we calculate the interaction between R&D expenses and number of patents received.

Product diversity was measured by assessing the diversity of products offered within each company, which taking both the sales figures of each product categories and number of product segments the companies are operating into account. Following the existing studies (Hitt *et al.*, 1997; Chakrabarty, 2015; He *et al.*, 2016), we calculated the product diversity scores through an entropy score. More specifically, the product diversity entropy can be defined in equation (5):

$$(5) \quad Product\ Diversity_l = \sum_{i=1}^M P_i \ln(1/P_i)$$

where P_i is the firm's sales percentage from the product segment I and M is the total number of the product segments that the company generating revenue income. We manually collected all the data from companies' annual reports.

Market diversity was measured by assessing the diversity of markets offered within each company. Similar to how we measure the product diversity, the market diversity captured the sales figures of different geographical regions in China and the total number of national geographical regions the companies operated in. The calculation of market diversity can be found in equation (6):

$$(6) \quad \text{Market Diversity}_I = \sum_{r=1}^K P_r \ln(1/P_r)$$

where P_r is the proportion of firm's sales attribute to a region of China r and K is the total number of the regions the companies were receiving the revenue income.

Environmental conditions. In this study, we use two measures of environmental conditions for the firm, environmental stability, and environmental munificence. Environmental stability refers to the rate of changes in factors relevant to strategic decision making (Duncan, 1972). Similar to Shen *et al.* (2010), the environmental stability is calculated as the variance of four-firm sales concentration ratio over a three-year period (from 2013 to 2015) at each observation's 2-digit SIC level. The environmental munificence denotes the extent to which industrial context is suitable for sustained firm growth. According to Porter (2004), a higher growth market represents a more abundant environment for a company. Therefore, to operationalise the environmental munificence, we calculated the regression slope coefficient (*beta*) of the RMB value of production for each observed 2-digit SIC industry during three years (from 2013 to 2015) (Goll and Rasheed, 2005). We followed Goll and Rasheed (2005)

to compute the regression slope using time as the dependent variable, and the RMB value of shipments as the independent variable. The data were obtained from the National Bureau of Statistics of the People's Republic of China.

3.2.3. Contingency variable – Measuring analytics capability

The conceptualisation of analytics capability is adopted from LaValle *et al.* (2011). Following the study of LaValle *et al.* (2011), three levels of analytics capability were identified - aspirational, experienced and transformed. Firms were classified on the basis of their capability in analytics. We extracted from the companies' annual reports¹ texts that delineate how an organisation has been transformed by the use of an analytic approach, or how analytics has been used to support business processes. By analysing these texts, we were able to evaluate the level of analytics capability for each organisation and then categorise them into four-degree levels, ranging from no evidence to show that analytics has been adopted (coded as 1), through aspirational (coded as 2 and considered as low level of analytics capability), experienced (coded as 3 and considered as medium level of analytics capability), and transformed (coded as 4 and considered as high level of analytics capability). Firms with no analytics capability excluded in our sample. For firms excluded in our sample, we also review their company annual reports for a three-year period (i.e. 2013-2015) to ensure no analytics-related practices were initiated.

Content analysis technique was used to classify a firm's analytics capability. Content analysis is an appropriate approach to analyse documents that have a clear structure and flow, such as companies' annual reports. Several studies have employed analysis of annual reports

¹ The annual reports used in this study were collected from the CNINFO website (www.cninfo.com.cn) maintained by Shenzhen Securities Information Co., Ltd.

or case materials to elaborate organisational performance related to the adoption of a specific technology (Peppard *et al.*, 2007) or a series of organisational activities (Lam *et al.*, 2016).

We followed the three-step coding process of preparation, organising, and reporting provided by Elo and Kyngäs (2008). The first step was to make sense of the coding process in terms of the coding unit of analysis, the level of analysis, and the purpose of evaluation. We selected themes as the coding unit of analysis, looking primarily for the expressions of an idea, which can be sentences, paragraphs, or a portion of a page. The level of analysis in this study is the organisation that engages in analytics technology implementation or analytics systems. The purpose of this coding process was to evaluate the level of analytics capability for each sample. After setting up the coding process, the next task was to define each level of analytics capability. The classification of analytics capability is adopted from LaValle *et al.* (2011). We then developed an explicit coding instruction that allows coders to be trained until reaching specific reliability requirements.

We recruited two coders who each have substantial research experience on analytics. One coder initiated the selection of texts used to serve as the basis for further analysis. A text was selected if it thoroughly explained: 1) how analytics tools or systems are adopted 2) how analytics capability helps firms' operations or business processes. The selected texts were given to another coder; both coders then followed the coding procedure to analyse each text independently. An Excel table with the analysis unit and all the elements listed was given to the coders to manage the texts extracted from the annual reports. We provide some coding examples in Table 1. In the coding process, the coders broke down, examined, and categorised each text into one of the four levels of analytics capability. An audit process was carried out to improve the accuracy of classification (Krippendorff, 2013). The two coders agreed on 88% of the classifications, which exceeds the recommended rate of 0.70 (Miles and Huberman, 1994).

Table 1. Coding examples of analytics capability¹

Analytics capability	Description	Text extracted from annual reports of sample companies
Aspirational level of analytics capability	Organisations with the aspirational level of analytics have a limited ability to capture, integrate and analyse data to acquire more profound business insights, due to a lack of data governance and information sharing culture.	<i>Henan Pinggao utilises a big data management platform to assist design and production and improve assembly capability.</i>
Experienced level of analytics capability	Organisations with the experience level of analytics have analytical experience along with better data governance and information sharing culture	<i>Xi'An Shaangu Power Company achieves inter-operability of the entire power equipment operation process and ecosystem by using a platform that integrates a cloud computing service and BDA techniques. This platform enables Xi'An Shaangu to manage the product life cycle, support computer numerical control (CNC) manufacturing of core components and remote automatic monitoring, provide predictive maintenance solutions for their customers, and eventually optimise organisational resource utilisation for product innovation.</i>
Transformed level of analytics capability	Organisations with a transformed level of analytics effectively use predictive and prescribe analytics to guide strategic actions.	<p><i>Great progress has been made in improving the unified logistics operating ability from the Company to the terminal, and in enhancing the monitoring and analysis ability in the management of big data relating to product sales and inventory throughout the process. In addition, the overall user experience has been intensified by means of the improved overlay network, response speed, service quality and “last kilometre” delivery ability.</i></p> <p><i>Guangdong Fenghua has developed a cloud computing platform that has gradually integrated big data resources between headquarters and subsidiaries. This platform has established and improved the risk and financial management, further enhanced the efficiency of sales management and human resource management, and eventually achieved standardisation of management processes.</i></p>

¹In order to provide insightful examples, we have rephrased text from the annual reports rather than use direct quotes. This is because the quotes are generally too long and difficult to comprehend. The selected texts in our examples were translated from Chinese to English.

3.3. fsQCA research design

To examine the configurations that shape a firm’s operational efficiency and income, fsQCA is used in this study to conduct the empirical analysis. The advantage of using the configurational approach resides in the fact that it tests if a condition or grouping of conditions is necessary and/or sufficient for the outcomes to be observed (Pappas and Woodside, 2021). This method of analysis is particularly useful to reveal patterns in the data (Ragin, 2008). The fsQCA methodology is applicable for both qualitative and quantitative data and is useful for

understanding the formations of conditions or constructs, based on set theoretic, which emerge from complex combinations (Ragin, 2008). The fsQCA has an advantage over regression analysis in that it can identify several potential combinations of explanatory variables (Fiss, 2011).

For the purpose of this study, knowledge absorptive capacity, SCG and environmental conditions are pooled together to observe their influence on operational efficiency and income. As potential configurations of these four explanatory variables are numerous (Ragin, 2008), the study does not specify in advance which configurations are likely to result in higher operational efficiency or income. The fsQCA approach helps in identifying multiple causations when it is likely that there are several configurations leading to higher operational efficiency or income (Grandori and Furnari, 2008). Authors have called this “*resource orchestration recipes for performance*” (Hughes *et al.*, 2018, p 1130).

Ragin and Davey’s fsQCA software (2016) is used in this study. Using this tool, we calibrate the data used in the study and examine this calibrated data for set membership (Ragin, 2008). For the measures where we combine two variables into a single calibrated value, like supply chain concentration, we use Boolean Algebra to reduce the two calibrated values into one measure. Using a fuzzy OR operation, we choose the higher of the two values. For example, in the case where supplier concentration is 0.7, and customer concentration is 0.6, we have a supply chain concentration value of 0.7.

The fsQCA has the advantage of variable calibration, which helps in identifying the observations and breakpoints relevant for the study. For this analysis, we adopted three key breakpoints, (1) full non-membership, (2) full membership, (3) cross-over point, which represent whether an observation is the member of the target set (Ragin, 2008; Cui *et al.*, 2017). Based on the minimum, maximum, and average values for each variable, we assigned the full non-membership, full membership, and cross-over points in our analysis. These calibration

values are shown in Table 2 (refer to the “Calibration points” column). Table 3 provides correlations of all the variables in the study.

Next, we considered the truth table based on the following two conditions: (1) the minimum number of observations for a given configuration (frequency threshold), (2) the minimum level of consistency for a given solution (Fiss, 2011). Following contemporary research in this area, we set the frequency threshold as 7 cases for each configuration and set the minimum level of consistency at 0.80 (Fiss, 2011). In the last step, we use the fsQCA software to simplify the configurations using the Boolean algorithm and use the intermediate solutions (Gilbert and Campbell, 2015).

Table 2. Summary statistics and calibration

Configurational elements and outcomes	Variables	Mean	S.D.	Anchors			Theoretical and empirical justification for calibration
				Max	Calibration points	Min	
Knowledge Absorptive Capacity	R&D expense	7.81	0.49	9.72	7.81	6.71	<ul style="list-style-type: none"> • Based on observed range of R&D expenditures among Chinese high-tech firms • Reflects absorptive capacity literature (Cohen & Levinthal, 1990; Roberts et al., 2012) where high R&D investment signifies strong knowledge assimilation ability.
	Total number of patents	16	80.15	1179	16	1	<ul style="list-style-type: none"> • Extreme values represent the industry's patenting dispersion. • Patent count as innovation output proxy in absorptive capacity (Tseng et al., 2011).
Supply Chain Concentration	Supplier concentration	30.39	15.15	97.16	30.39	0.13	<ul style="list-style-type: none"> • Values derived from Herfindahl–Hirschman Index distribution. • Higher concentration indicates formal control and dependency per Resource Dependence Theory (Pfeffer & Salancik, 2003; Lanier et al., 2010).
	Customer concentration	31.79	18.70	97.43	31.79	3.08	<ul style="list-style-type: none"> • Reflects the top-customer revenue contribution pattern from annual reports. • Represents decision-rights dependence structure (Saboo et al., 2017).
Diversification	Product diversity	0.98	0.47	2.55	0.98	0.00	<ul style="list-style-type: none"> • Entropy-based index using product segment data. • Strategic diversification logic, economies of scope and coordination mechanisms (Tallman & Li, 1996; Zahavi & Lavie, 2013).
	Market diversity	0.25	0.24	1	0.25	0.00	<ul style="list-style-type: none"> • Entropy index of geographic sales distribution. • Market diversity relates to relational governance and adaptation needs (Gnyawali et al., 2006).
Environmental conditions	Environmental stability	0.29	0.27	0.90	0.29	0.00	<ul style="list-style-type: none"> • Calculated from variance of four-firm sales concentration • Represents predictability of external conditions (Duncan, 1972; Sitkin et al., 1994).
	Environmental munificence	2.57	1.36	7.68	2.57	1.38	<ul style="list-style-type: none"> • Regression slope of industry output over time (Goll & Rasheed, 2005). • Reflects availability of growth opportunities and resources (Castrogiovanni, 1991).
Operational performance	Operational efficiency	0.79	0.15	9.72	0.79	0.19	<ul style="list-style-type: none"> • Calculated via stochastic frontier estimation (Lam et al., 2016). • Measures firm's relative efficiency frontier (Vandaie & Zaheer, 2015).
	Operational income	20.65	1.31	25.35	20.65	17.68	<ul style="list-style-type: none"> • Firm-level accounting data from CSMAR. • Proxy for operational performance outcomes in analytics–performance literature (Srinivasan & Swink, 2018; Wang et al., 2018).

Table 3. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10
1. Operational efficiency	1.000									
2. Operational Income	0.208*	1.000								
3. R&D expense	-0.036*	0.838*	1.000							
4. Total amounts of patent	0.033*	0.298*	0.347*	1.000						
5. Supplier concentration	0.079*	-0.114*	-0.224*	-0.119*	1.000					
6. Customer concentration	0.370*	0.059*	-0.053*	-0.042*	0.192*	1.000				
7. Product diversity	-0.004	-0.027*	-0.027*	-0.001	-0.225*	-0.118*	1.000			
8. Market diversity	0.181*	0.250*	0.223*	0.082*	0.007	0.202*	-0.147*	1.000		
9. Environmental stability	0.200*	0.080*	0.054*	0.042*	0.160*	0.121*	-0.276*	0.203*	1.000	
10. Environmental munificence	-0.286*	-0.205*	-0.118*	0.000	-0.130*	-0.125*	0.260*	-0.188*	-0.628*	1.000

* $p < 0.1$

4. RESULTS

In all our results tables – Tables 4, 5, and 6, we observe that overall solution coverage is higher than the sum of individual unique coverages, indicating an overlap between the configurations. There are a different number of configurations for different levels of analytics, and though there is some overlap between the models at different levels. We also observe some unique configurations for each level of analytics.

Configurations of aspirational analytics capability (See Table 4). We found the essential roles of diversification and environmental conditions (i.e., when environmental munificence and stability are high) are indicated in the high operational efficiency and high operational income. Similarly, the non-essential role of knowledge absorptive capacity and concentration for high operational income outcomes is also detected in these analyses.

Configurations of experienced analytics capability (See Table 5) In the case of both operational efficiency and operational income, the essential role of environmental conditions (i.e., when environmental munificence and stability are high) is detected. For operational efficiency, the non-essential roles of knowledge absorptive capacity, supply chain concentration, and diversification are indicated. On the other hand, for operational income, we

observe the essential role of knowledge absorptive capacity along with that of environmental conditions and the non-essential role of supply chain concentration and diversification.

Configurations of transformed analytics capability (See Table 6). Unlike models at the other two levels of analytics capability, no essential or central conditions are identified across both the performance outcomes, though we observe the essential role of only knowledge absorptive capacity for operational income. We also find two configurations that demonstrate the absence of the supply chain concentration factor in their configurational outcomes as well as other configurations with the presence of concentration in the non-essential role. This higher degree of environmental munificence and stability in the configurations can indicate the highly idiosyncratic nature of high operational performance.

Figure 3 depicts the conceptual 3×3 framework that consolidates these configurational findings. The framework maps analytics capability maturity (aspirational, experienced, and transformed) against the three key structural dimensions: organisational capability, governance mechanisms, and environmental context. It visually illustrates how the dominant performance drivers evolve as analytics capability matures—from reliance on diversification and stable environments (aspirational), to the strengthening of absorptive capacity and concentrated governance ties (experienced), and finally to adaptive knowledge orchestration and innovation governance in complex environments (transformed). This integrative visual not only summarises the fsQCA results but also generalises them into a broader theoretical model that captures how analytics capability interacts with organisational and environmental structures to achieve operational excellence.

Table 4. Configurational solutions for aspirational analytics capability

	Operational Efficiency	Operational Income	
Configurational conditions	Solution (1)	Solution (1)	Solution (2)
Knowledge absorptive capacity		•	
Supply chain concentration			•
Diversification	●	●	●

Environmental conditions	●	●	●
Consistency	0.69	0.82	0.78
Raw coverage	0.86	0.80	0.68
Unique coverage	0.86	0.13	0.01
Overall solution consistency	0.86	0.81	
Overall solution coverage	0.86	0.81	

Note: The large black circles (“●”) suggest “core” or central conditions, and small black circles (“•”) indicate “periphery” or contributing conditions. The blank spaces show “don’t care”, meaning the condition is not pertinent to that particular configuration (it may be either present or absent).

Table 5. Configurational solutions for experienced analytics capability

Configurational conditions	Operational Efficiency			Operational Income	
	Solution (1)	Solution (2)	Solution (3)	Solution (1)	Solution (2)
Knowledge absorptive capacity	•	•		●	●
Supply chain concentration	•		•	•	
Diversification		•	•		•
Environmental conditions	●	●	●	●	●
Consistency	0.82	0.78	0.83	0.84	0.83
Raw coverage	0.80	0.82	0.83	0.73	0.79
Unique coverage	0.03	0.06	0.07	0.04	0.10
Overall solution consistency	0.88			0.87	
Overall solution coverage	0.94			0.84	

Note: The large black circles (“●”) suggest “core” or central conditions, and small black circles (“•”) indicate “periphery” or contributing conditions. The blank spaces show “don’t care”, meaning the condition is not pertinent to that particular configuration (it may be either present or absent).

Table 6. Configurational solutions for transformed analytics capability

Configuration	Operational Efficiency			Operational Income	
	Solution (1)	Solution (2)	Solution (3)	Solution (1)	Solution (2)
Knowledge absorptive capacity	•	•		●	●
Supply chain concentration	○	•	•	○	•
Diversification	•		•	•	

Environmental conditions		●	●		●
Consistency	0.89	0.86	0.86	0.91	0.85
Raw coverage	0.65	0.76	0.79	0.59	0.67
Unique coverage	0.09	0.06	0.09	0.11	0.19
Overall solution consistency	0.90			0.88	
Overall solution coverage	0.95			0.79	

Note: The large black circles (“●”) suggest “core” or central conditions, and small black circles (“•”) indicate “periphery” or contributing conditions. The blank spaces show “don’t care”, meaning the condition is not pertinent to that particular configuration (it may be either present or absent). Open (“O”) circles indicate its absence.

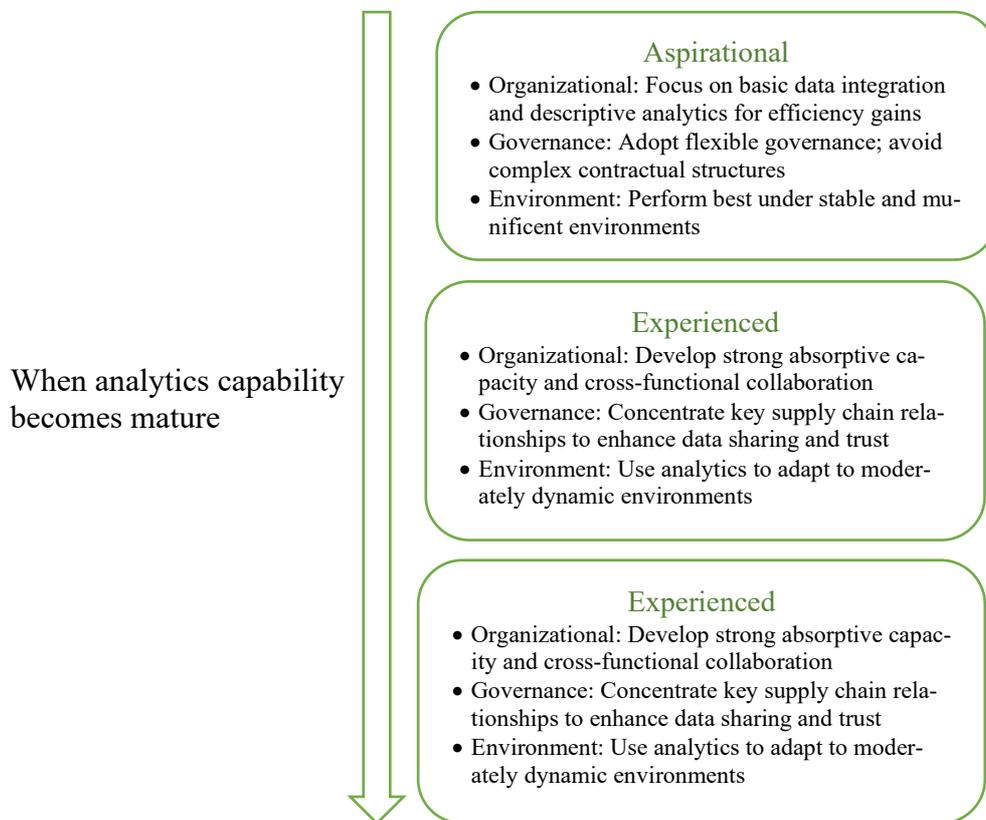


Figure 3. Conceptual 3x3 framework: analytics capability against three structural dimensions

5. DISCUSSION

5.1. Theoretical propositions for analytics technology implementation

By verifying a theoretical model that developed based on both complexity theory and contingency theory, this study obtains useful empirical results associated with analytics

technology implementation. Using analytics capability as a contingency condition, this study shows that firms with different levels of analytics capability need to apply specific organisational capability, SCG mechanisms, and environmental conditions to achieve operational performance. Based on the fsQCA results, we propose the following theoretical propositions specific to the different levels of analytics capability.

Aspirational level of analytics capability. As configurations shown in Table 4, high product and market diversity are necessary conditions for facilitating operational income and efficiency for firms with aspirational analytics capability. Firms with the aspirational level of analytics capability mainly focus on utilising descriptive analytics to tackle the problems within a functional unit, for example, improving the efficiency of existing operational processes or searching for a solution to reduce operational costs. With this analytics capability requiring low computational power and simple algorithm, firms should engage in diversification strategies in order to exploit synergies across product lines or markets and improve learning curve efficiencies in production process that could complement their analytical capability. Prior research has argued that IT spending interacts with diversification to have a positive effect on firm performance (Ravichandran et al., 2009). However, the effects of IT (e.g., what kind of IT should invest) have not been considered in their study. Our findings discovered from fsQCA extend Ravichandran et al.'s (2009) work by providing a novel insight in the analytics context that with aspirational level of analytics capability, interacting with diversification can improve firms' operational income and efficiency.

Moreover, in highly unpredictable business environments, firms will find it difficult to interpret the unpredictable events effectively, even with the use of business analytics (Park et al., 2017). In contrast, when instability in the business environment is low, firms are better able to explore the opportunity to improve their operations and have more time to devote to the deployment of analytics. In line with this, we argue that firms with aspirational level of

analytics capability can gain improved operational performance when the business environment is stable and munificence. Another argument would be that with their limited capacity to conduct sophisticated environmental scanning or deploying a full range of IT capability; these aspirational analytics firms perform best in a stable and munificent environment. This proposition is not in accordance with the claims of Neirotti and Paolucci (2011), where they suggest that in the munificent environment, companies usually invest more heavily in IT as there being more available resources and a stronger need to analyse a significant amount of information to scale up their operations.

Proposition 1(a): *For firms with aspirational level of analytics capability, diversification of product and market as necessary conditions fundamentally drives firms to achieve higher operational income and efficiency.*

Proposition 1(b): *Firms with aspirational level of analytics capability would gain superior operational performance when the industrial environment they operate is stable and munificence.*

Experienced level of analytics capability. Experienced level of analytics capability, made possible by better data governance and sharing culture, enables organisations to guide actions by using rigorous analytical approaches. At this level, data can be collected across a broad range of functions and analysed in a meaningful way to generate insights to drive superior business value. This level of analytics capability allows organisations to address more complex problems relating to strategy development, customer and supplier service, and new product development.

Based on the results of fsQCA, firms with experienced level of analytics capability should emphasise on developing their knowledge absorptive capability in order to leverage analytics for better operational performance. As mentioned, knowledge absorptive capacity enables

firms to identify IT capability. Such a capacity is particularly useful for the firm with the experienced level of analytics capability as it provides an opportunity for firms to speed up their analytics enabled decision-making processes (Wang and Byrd, 2017).

Moreover, higher supply chain concentration, where the distribution of a firm's revenue is focused on a small number of customers and suppliers, can help experienced analytics firms to facilitate operational performance. This proposition is supported by the resource dependence theory, which argues that when companies lack essential resources, they will strive to establish stable relationships with others in order to obtain the resources needed to achieve their desired organisational performance (Pfeffer and Salancik, 2003). Singh *et al.* (2011) argue that the inter-organisational relationship described by resource dependence theory can be expressed as coalitions being formed to manage the uncertainty. Companies that focus on a few major customers and suppliers will be more capable of managing supply chain relationship and reducing transaction costs (Saboo *et al.*, 2017). Therefore, firms with experienced level of analytics capability should adopt concentration strategy for their supply chain so as to acquire the necessary resources (such as customer profiles and daily transaction data) to strengthen the effectiveness of analytics in achieving superior operational performance.

Proposition 2(a): *For experienced analytics firms, to increase operational income, strong knowledge absorptive capacity and high level of environmental munificence and stability should be central in configurations and simultaneously complemented by appropriate SCG mechanisms (either high in diversity or high in supply chain concentration).*

Proposition 2(b): *For firms with experienced level of analytics capability, to achieve operational efficiency, high level of environmental munificence and stability should be central in configurations and should be complemented by at least two out of the three other elements.*

Transformed level of analytics capability. Transformed analytics firms have ability to use advanced analytics (e.g., predictive and prescribe analytics) to prescribe strategic actions. Using predictive modelling and algorithms, predictive analytics can explore undetected correlations and patterns between current and historical data and identify future possibilities and trends (Sivarajah et al., 2017). Prescriptive analytics can optimise and simulate plausible options for future business decisions by using real-time data and mathematical algorithms (Sivarajah et al., 2017). For example, an online retailer, Rue La La, used machine learning techniques to develop a demand forecasting system that predicts demand for newly launched products and optimises its pricing decisions. This demand forecasting system has helped Rue La La to improve revenue by 9.7% (Ferreira et al., 2015).

Based on the fsQCA results shown in Table 6, we provide novel insights of how firms with transformed level of analytics capability can orchestrate their internal and external resources. Remarkably, the role of knowledge absorptive capacity is rather important for increasing operational income as it plays a pivotal role in transforming business insights induced by analytics into business value (Wang and Byrd, 2017). Likewise, Ross et al. (2013) suggest analytics cannot be fully functioned until an organisation cultivates the ability to assimilate and transform knowledge discovered by analytics systems. Thus, we argue that when transformed analytics organisations are more focused on knowledge absorption, operational income can be maximised.

Moreover, for transformed analytics organisations, all of the proposed elements appear as a peripheral condition in all solutions for high operational efficiency. Although these elements are not necessary, firms require the presence of at least two elements such as knowledge absorptive capacity and diversification as complementary condition for improving operational performance. We therefore propose the following proposition.

Proposition 3(a): *For firms with transformed level of analytics capability, knowledge absorptive capability is essential to achieve high operational income.*

Proposition 3(b): *All of the elements could play a complementary role (or in some cases, is not necessary role) for achieving higher operational efficiency when firms have a transformed level of analytics capability.*

5.2. Theoretical and managerial implications

Analytics capability is widely acknowledged as an essential factor for the company to achieve superior supply chain performance. While many studies have claimed that with enhanced analytics capability, firms are expected to make better predictions towards the uncertainty and, therefore, positively influence operational performance. Nevertheless, what seems to be missing in the extant literature is to answer the question of *how internal and external exogenous resources can be effectively orchestrated to drive operational performance for firms under different levels of analytics capability*. Our findings offer novel insights based on the configurational approach and provide several implications, as discussed below.

First, previous studies of developing analytics capability have mainly adopted the resource-based view of a firm's information capability, where analytics capability is conceptualised by orchestrating tangible and intangible resources of analytics. Our study departs from this stream of research in that we take the LaValle *et al.* (2011) classification of analytics capability and conceptualise it as three distinct capability levels based on the motive for adoption, functional proficiency, data management, and analytics in action. This classification of analytics capability could be a useful approach to evaluate firms' analytic prowess and identify their stage of analytics adoption and implementation. Moreover, we treat analytics capability as a contingency condition in configurations. This will help us generate configurational solutions specific to firms under different levels of analytics capability.

Second, prior research has often viewed analytics as a technical or an organisation and process issue (Srinivasan and Swink, 2018). For instance, Ross *et al.* (2013) suggest that an organisational culture of evidence-based decision making enables firms to ensure the decision-making quality, thereby improving overall firm performance. However, a discussion regarding how the SCG influences the implementation of analytics is noticeably absent from the existing literature. We employ the lens of complexity theory with the objective of understanding in-depth how firms' social chain governance conditions might associate operational performance under different levels of analytics capability. By doing so, this study is one of the first empirical studies elaborate on the effects of SCG in the context of analytics capability.

Third, we explore the complex dynamics of analytics implementation with a configurational approach. While previous studies have focused the leaner net-effects of analytics on performance, this study examines under what organisational, supply chain, and environment conditions firms can combine to achieve operational performance. By doing so, we reveal multiple "secret recipes" of successful analytics technology implementation to firms under different levels of analytics capability. These findings are aligned with the propositions of CT about the importance of understanding the interplay between the internal contingency (i.e. analytics capability) and the external environment.

The findings of this study also have implications for managerial practice. We highlight that analytics capability exerts a contingency effect on operational performance. Building on this, Table 7 offers actionable guidance for firms at different stages of analytics maturity by aligning strategic focus, governance priorities, organisational capabilities, and environmental strategies. For example, firms at an aspirational level should diversify their product and market scope while maintaining flexible governance structures and operating in stable, resource-abundant environments. Experienced firms should emphasise strengthening absorptive capacity, deepening coordination with key supply chain partners, and leveraging analytics to

navigate moderately dynamic environments. Finally, transformed firms should leverage predictive and prescriptive analytics for strategic agility, focusing less on governance constraints and more on knowledge sharing and innovation orchestration within complex environments. Collectively, this matrix enables firms to orchestrate their organisational, supply chain, and environmental resources effectively to achieve analytics-driven operational excellence.

Table 7. Managerial implications by analytics capability level

Analytics capability level	Strategic focus	Supply chain governance Priority	Organisational capability emphasis	Environmental strategy
Aspirational	Diversify product and market scope to exploit synergies and learning economies.	Maintain flexible but simple governance; avoid over-contracting with few partners.	Develop foundational data integration and analytics literacy	Operate best under stable and resource-abundant environments
Experienced	Strengthen absorptive capacity and cross-functional coordination.	Concentrate key supplier/customer relationships for efficient data sharing and trust building.	Invest in knowledge management systems to leverage analytics insights	Use analytics to navigate moderately dynamic environments
Transformed	Leverage predictive and prescriptive analytics for strategic agility and innovation.	Governance structure becomes less critical; focus on orchestration and innovation networks.	Deepen knowledge absorption, promote organization-wide learning.	Exploit complex, changing environments as opportunities for innovation and experimentation

5.3. Limitations and directions for future research

In common with other studies that utilise secondary data, this study suffers from several limitations regarding the measurements. *First*, the proxies of analytics capability were measured by data obtained from the companies’ annual reports. However, there might be a gap between the disclosure of analytics projects and real analytics practices. How to use secondary data from other sources to measure the analytics capability could be a worthwhile topic for future studies. Moreover, future research could further enhance the validity of analytics capability measurement by employing external validation methods. For instance, triangulating content analysis results with interviews or surveys of firm managers could help reduce

subjective bias in manual classification and provide richer contextual understanding of how analytics capabilities are enacted in practice.

Second, our analysis took into consideration only the data for over a certain period of time (from 2015 to 2016). Although we could not explore the complexity dynamics of analytics technology implementation over time due to data limitations, the fsQCA approach allows us to examine how firms evolve from aspirational-level to transformed-level of analytics capability by orchestrating organisational capability, SCG, and environmental conditions. Future research could adopt a longitudinal comparison to understand the evolution of analytics capability and the changes in the relationship between conformational elements and operational performance.

Finally, although our sample focuses on listed high-tech firms in China, future studies could extend this research by examining non-listed firms and organizations from other industries and national contexts. Testing the proposed configurational model across diverse economic and regulatory environments would allow researchers to assess the robustness and boundary conditions of the identified relationships and offer a more comprehensive understanding of analytics-driven operational excellence.

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