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Data-driven market effectiveness: The role of a sustained customer analytics capability in business operations

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ABSTRACT

This study's objective is to investigate how a business can achieve data-driven market effectiveness through the sustained application of a customer analytics capability to its operations. Despite the abundance of literature on retail technology management, empirical evidence on the effectiveness of a customer analytics capability in promoting sustainable market performance within retail business operations remains scarce. This study presents a model of a sustained customer analytics capability in the context of competitive, data-rich retail business processes, drawing on grounded market orientation capability theory. The study employs a taxonomy of explanation and prediction from an epistemological perspective, employing predominantly positivist methods, where data analysis validates the conceptual customer analytics capability and its sustained critical outcomes. In addition, the study discusses the significant contributions of its findings regarding the acceleration of retail business operational performance in a big data environment and also provides future research directions to resolve any limitations of the current study.

1. Introduction

Technological advancements in the modern, data-rich business environment have fundamentally transformed the traditional methods of conducting business (Jonsson et al., 2018; Nayak and Walton, 2023). Hence, firms need to be agile in adopting digital technologies as part of their operations (Correani et al., 2020). In this competitive business environment, it is essential to establish sustainable processes, as the traditional approaches may not suit the current, data-rich ecosystem. It is important to note that the vast quantity of available data can provide valuable insights for businesses seeking to implement sustainable operations (Acciarini et al., 2023; Wedel and Kannan, 2016). A data-driven consumer analytics capability is essential for sustaining a competitive edge within business operations (Diorio, 2020; Hunke et al., 2022). The retail industry is uniquely positioned to collect voluminous customer data, making the extensive use of customer analytics within business operations advantageous for retailers (Germann et al., 2014; Kitchens et al., 2018). Despite the importance of a customer analytics capability within data-rich business operations, the majority of practitioners are unaware which factors are required to generate market effectiveness in the modern, competitive, data-driven environment (Inman and Nikolova, 2017; Weinswig, 2018).

The existing academic research on sustainable business operations reveals concepts that are fragmented across industries. Belhadi et al. (2021) utilised supply chain resilience theory to clarify the operations of automobiles and airlines during a pandemic. Kamble et al. (2021a, 2021b) created a decision support system that employs machine learning techniques to predict an organisation's likelihood of adopting block chain successfully. Hu et al. (2021) created a model for selecting industries that control carbon emissions using the controllability theory of complex networks. Shen et al. (2021) identified the value of supply chain innovation, which allows upstream suppliers and downstream manufacturers to co-develop products containing multiple innovative components. In addition, Cai et al. (2021) conducted an in-depth analysis of the operational difficulties within the fashion retail supply chain related to the collection of used apparel. Using a large group decision-making technique, Kamble et al. (2021a, 2021b) identified and ranked the best big data-driven sustainable sharing economy practices in the automotive industry. Despite the widespread market success of sustainable customer analytics operations, there remains a paucity of

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empirical research on the topic.

The theoretical formulations in the field of information systems (IS) operations research involve four interrelated classes: domain-based, structural or ontological, epistemological, and socio-political (Gregor, 2006; Kar and Dwivedi, 2020). Scholars suggest that domain questions are concerned with identifying the phenomena of interest, while ontological questions seek to understand how theoretical terms are understood within the discipline. Epistemological questions focus on how theory is constructed, while socio-political questions examine how the stakeholders understand disciplinary knowledge within the context of human affairs.

This study employs the taxonomy of explanation and prediction (Gregor, 2006) to explain the antecedents and predict the results of constructing the facts and predicting subsequent events. According to Harrington (2005, p. 5), "Theories without data are empty; data without theories are blind," a quote which is attributed to the 18th-century scholar Immanuel Kant.

There is evidence to suggest that the retail industry generates a large volume of market data, so analysing this data in business operations can help retailers to provide value to both current and potential customers. Previous studies indicate that retail firms can enhance their sustainable performance by developing a value-centric customer analytics capability (Hossain et al., 2020). Consequently, it is essential to develop and empirically test a comprehensive theoretical model that incorporates all of the value-centric antecedents and outcomes of a consumer analytics capability. The theoretical taxonomy of explanation and prediction demonstrates what will be predicted, as well as when, how, and why, based on causal explanations and testable propositions (Gregor, 2006).

The existing research on analytics has introduced the concept of the resource-based view (RBV) as a means of theorising firms' capability-centric models (Gupta and George, 2016; Santiago Rivera and Shanks, 2015). RBV recognises valuable, rare, inimitable, and non-substitutable (VRIN) resources as crucial for attaining competitive performance in the marketplace (Barney, 1991). The landscape of analytics-driven operations and information systems (IS) is continuously evolving, however, in response to marketplace changes (Davenport et al., 2020; Inman and Nikolova, 2017). As a result, relying solely on RBV may be insufficient to satisfy fully the requirements of the end consumers. Consequently, this study augments the theoretical foundation of RBV by introducing a market orientation capability as a means of advancing the theoretical foundation of a customer analytics capability. The purpose of this study, based on the preceding discussion, is to address the following research question:

RQ: How can a firm achieve data-driven market effectiveness by utilising a sustained customer analytics capability within its business operations?

Despite the increasing importance of customer analytics functions in sustaining organisational operations, the literature on this aspect remains fragmented and inadequate, and also fails to explore the overall conceptualisation. This study makes several contributions by introducing the market orientation capability theoretical view. First, the study provides a theoretical model for understanding a sustained customer analytics capability by integrating the value mechanisms into operations management. Second, although earlier research shows the impact of an analytics capability on firm performance (Dubey et al., 2019; Gupta et al., 2020), this study enhances these findings by showing how an analytics capability becomes effective in the market through improving customer relationship performance. Third, while extant studies acknowledge the importance of customer relationship management in the business field (Libai et al., 2020; Verhoef et al., 2010), they fail to demonstrate the significant role that customer relationship performance plays in mediating between a firm's analytics capability and its overall market effectiveness. Finally, this study advocates practices that educate managers regarding the prerequisites and implications of a strong customer analytics capability in terms of retail business operations management. The purpose of the study is to guide the development of a model for a sustained customer analytics capability in the retail industry in order to ensure its long-term viability. The study also examines the impact of a sustained customer analytics capability on market effectiveness.

The subsequent sections of this study are organised as follows. Section two provides an overview of the contextual research gap. Section three establishes the theoretical foundation, research framework, and hypotheses. Section four discusses the methods employed for the data collection and analysis. Section five presents the study's findings. Section six serves as the conclusion of the study and addresses the contributions of the research, its limitations, and the future research agenda.

2. Contextual research gap

A preliminary search of the major databases using the terms 'analytics capability' and 'business operations' yielded a substantial number of articles covering the period from 2010 to 2021. To ensure the quality of the articles, the researchers examined the citations, the quality of the journals, and the impact of the articles on the academic literature, then reviewed each article in depth to determine whether or not it met the benchmark standard. Table 1 presents a list of the articles that were identified as being related to the study theme. The majority of these studies focused on a big data analytics capability in the manufacturing industry, and were conducted in the USA, Czech Republic, India, and Norway (Awan et al., 2021; Dubey et al., 2019; Mikalef and Krogstie, 2020). One study collected survey data on an analytics empowerment capability in the Australian service industry (Akter et al., 2021), while another focused on a service system analytics capability within the USA service industry (Akter et al., 2020). Two studies considered a business analytics capability (Cosic et al., 2012; Cosic et al., 2015), while a further two studies investigated a marketing analytics capability in the UK and Bangladesh, respectively (Cao et al., 2019b; Rahman et al., 2021). Overall, the existing studies have failed to address the research gap regarding how retail firms can establish a sustained customer analytics capability (CAC) in order to enhance their market efficacy. Table 1 provides a summary of the relevant articles identified.

3. Theoretical underpinning and hypotheses development

The existing concept of RBV guides firms to use both their tangible and intangible resources to achieve good operational performance (Barney, 1991; Zahra, 2021). Scholars have also acknowledged that a firm's resources may become significant if the firm's foundation is sufficiently strong to integrate valuable, rare, inimitable, and non-substitutable resources to create benefits for both society and customers (Huang and Chen, 2023; Wernerfelt, 1984). Firms should identify the appropriate resources and capabilities that influence the overall process in order to create value for their customers (Nenonen et al., 2019; Ngo and O'Cass, 2012). A firm's ability to maintain resources is more critical than its total resource levels with regard to facilitating excellent performance in the marketplace (Lovallo et al., 2020; Vorhies et al., 2009). However, RBV has not yet fully classified the crucial activities that require the value-centric market-focused resources in operations. Thus, the overall traditional theoretical view needs to be remodelled in order to generate insights from big data (Dubey et al., 2019; Viaene, 2013).

Sutton and Staw (1995) offer a definition of theory as the connections among phenomena, as a story about why acts, events, structure, and thoughts occur. To build theory, it is necessary to design, conduct, and interpret hypothetical experiments in a way that is explicit and self-aware, in order to delineate the theorising process (Sullivan, 2020; Weick, 1989). Theoretical epistemological beliefs play a crucial role in identifying the process of theory construction, including the development of knowledge within the theory, methods for testing the theory and achieving soundness, and rigorous process (Gregor, 2006). All of these epistemological issues must be addressed in order to theorise a market

Table 1
An analytics capability within business operations: research contexts and the research gap.

Author(s)	Nature of evidence	Country of data collection	Research Context	CAC attachment in business operations	Scope of researching sustained CAC in retailing
(Akter et al., 2021)	Quantitative, 245 survey data	Australia	An analytics empowerment capability in service industry operation	No	Yes
(Akter et al., 2020)	Quantitative, 251 survey data	USA	A service system analytics capability in service industry operation	No	Yes
(Akter et al., 2016)	Quantitative, 152 survey data	USA	A big data analytics capability investigation of multiple industries	No	Yes
(Awan et al., 2021)	Quantitative, 109 survey data	Czech Republic	A big data analytics capability in manufacturing industry operation	No	Yes
(Cao et al., 2019b)	Quantitative, 221 survey data	UK	Marketing analysis of a dynamic capability in a multi-industry context	No	Yes
(Cosic et al., 2015)	Qualitative, 3 round Delphi studies	N/A	A business analytics capability (industry not specified)	No	Yes
(Cosic et al., 2012)	Conceptual	N/A	A business analytics capability (industry not specified)	No	Yes
(Dubey et al., 2019)	Quantitative, 173 survey data	India	A big data analytics capability in the Auto components manufacturing industry	No	Yes
(Gupta and George, 2016)	Quantitative, total of 340 survey data	USA	A big data analytics capability in the service, retail, and manufacturing industry	No	Yes
(Gupta et al., 2020)	Quantitative, 209 usable sample	India	Big data predictive analytics: a dynamic capability view of business operations	No	Yes
(Kristoffersen et al., 2021)	Qualitative, 15 semi-structured interview	N/A	Business analytics capability: the circular economy	No	Yes
(Mikalef et al., 2017)	Case study approach	Multi-country international firms	A big data analytics capability in firm operations	No	Yes
(Mikalef and Krogstie, 2020)	Quantitative, 202 survey data	Norway	A big data analytics capability and competitive performance	No	Yes
(Rahman et al., 2021)	Quantitative, 250 survey data	BD	A marketing analytics capability in large, and medium manufacturing and service firms	No	Yes

orientation capability in the operations management information system (e.g., customer analytics). The theory that is applied to an information system has been classified into five types: Type I - analysis, Type II - explanation, Type III - prediction, Type IV - explanation and prediction, and Type V - comprehensive and design. This study adopts the Type IV taxonomy, which links the explanation to human understanding and aims to induce a subjective state of knowledge while, at the same time, predicting the consequences (Gregor, 2006; LaPlaca and da Silva, 2016). Kelemen (2019) and Tsang (2009) suggest that a theory's mechanistic explanations are typically based on assumptions, particularly those the lie at the root of beliefs. Therefore, unrealistic assumptions may lead to incorrect explanations and inaccurate predictions, so the realism of an assumption should be tested against the theory's hypotheses (Saylors and Trafimow, 2021; Shugan, 2007).

Following the above guidelines, and in line with relevant literature, we found that a market-focused firm with an appropriate capability can rapidly identify the customers' desires regarding the market and is likely to be capable of meeting the customers' expectations (Ngo and O'Cass, 2012). A firm with a market orientation places greater weight on discovering both the known and unknown underlying desires of the customers (Bhattacharya et al., 2019). The traditional view of the company and its operations differs radically from that of a market-oriented company. A conventional firm employs an inside-out strategy, in which internal resources are addressed initially, followed by an examination of the external market opportunities (Day, 2011). However, in the modern business environment, that is dominated by big data, the market is dynamic and rapidly changing. In an ever-changing business environment, the balance of power typically shifts to the consumer; therefore, analysing customer data is essential for monitoring the current market demand. This is why an outside-in perspective is gaining popularity, wherein a company should first consider the condition of the external market (Day, 2011; Day and Moorman, 2010). Consequently, the market-oriented activities of a company use the customer demand from the market in order accurately to detect the market conditions (Jaworski and Kohli, 1993; Ketchen Jr et al., 2007; Alnawas and Hemsley-Brown, 2019; Adams et al., 2019). Consequently, market-oriented businesses can generate and manage the value within their operations in order to engage with more customers, strengthen their relationships with their customers, and build trust (Day and Moorman, 2010). The following section demonstrates how the theoretical perspective of a market orientation capability explains a company's customer value-centric analytics capability within its operations and also predicts the customer relationship performance and market effectiveness in a big data-oriented, competitive retail business environment.

3.1. Proposed theoretical framework

The purpose of this study is to develop a method by which a company can accomplish data-driven market effectiveness by integrating customer analytics into its business operations. This paper identified a research gap in this area, which is discussed in Section 2. Therefore, based on the theoretical paradigm of a market orientation capability (Alnawas and Hemsley-Brown, 2019; Aydin, 2021), and following the direction of the higher-order model formulation from top-tier studies (Becker et al., 2012), this study proposes that a capability for creating, delivering, and managing customer value is critical for building a firm's sustained customer analytics capability. In turn, this may lead to improved customer relationship performance and so, ultimately, enhanced market effectiveness (see Fig. 1). Market orientation capability is a theoretical concept that enables companies to establish distinct outside-in value-centric factors within the organisation, which can contribute to higher performance (such as customer relationship performance and market effectiveness) in the long run (Aydin, 2021; Bhattarai et al., 2019; Novandari, 2019).

3.2. Customer analytics capability and market effectiveness

Big data analytics plays a significant role in advanced business activities that involve processing a large amount of non-personal data (Braun and Garriga, 2018). Although big data analytics has gained considerable importance, it is challenging to generate customer-centric value using such an unfocused analysis (Kitchens et al., 2018). Hence, customer analytics has gained popularity within business operations (Gray, 2021; Kitchens et al., 2018), offering retailers numerous

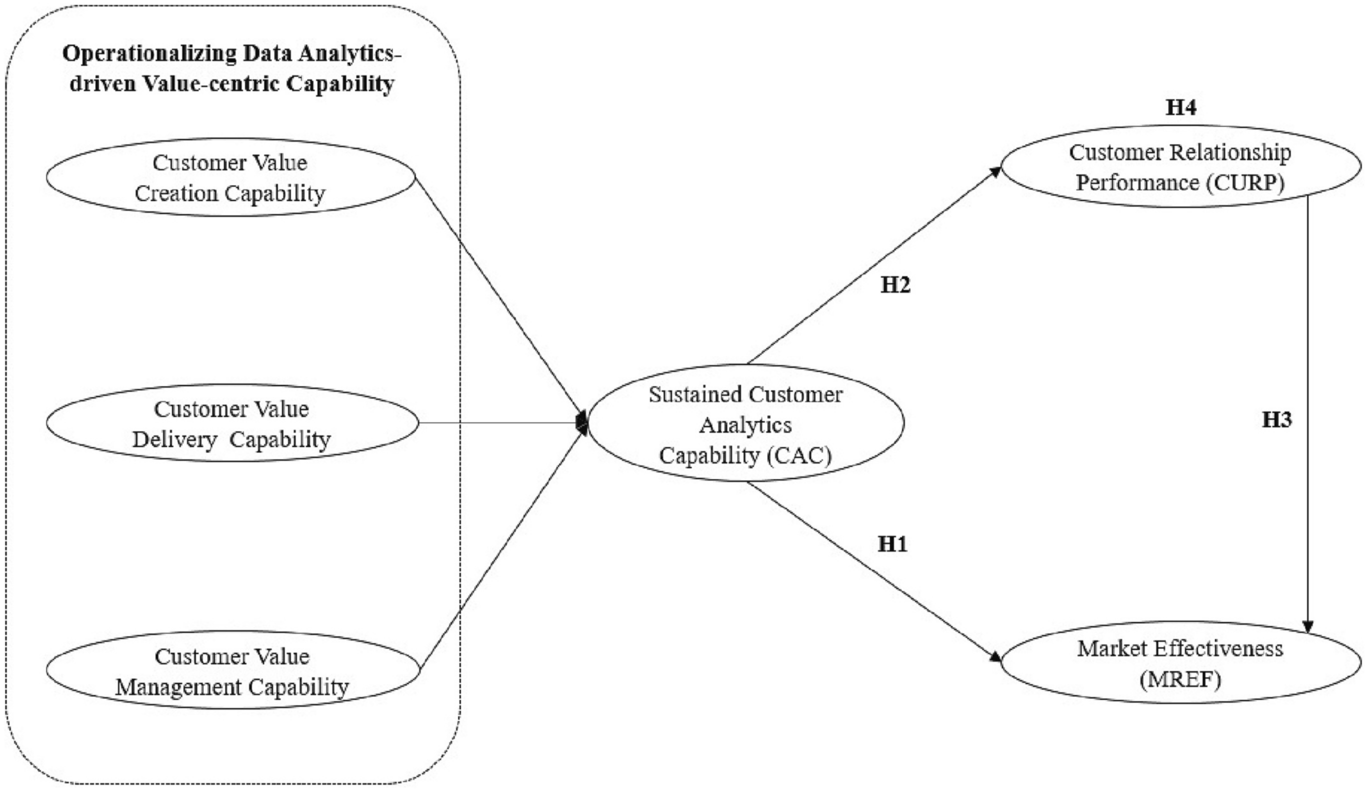

Fig. 1. Research model.

opportunities to capture customer insights effectively (Germann et al., 2014). Through adopting a market-oriented view, a firm can establish a sustained customer analytics capability by ensuring the creation, delivery, and management of customer value, based on the market demands and customer needs.

A firm's activities in creating customer value lies at the core of the business (Smith and Colgate, 2007), and scholars have frequently recognized it as the central task of a firm since its inception (Weinstein, 2018; Woodruff, 1997). Within business operations, it is possible to generate value by anticipating the current trends, customising products or services, and introducing suitable offerings. Hossain et al. (2020) advocate that a customer-centric analytics-driven value creation capability can ensure the desired outcome and accelerate the delivery of value by maintaining consistent processes, providing pertinent information, and answering customer enquiries across multiple channels. The analytics-centric value management capability has become a necessity in the contemporary business environment (Grover et al., 2018). A firm's relevant customer-centric capability may integrate customer data, protect customer information, and ensure security across multiple channels (Nam et al., 2019; Wang et al., 2020). Theoretically, these customer analytics capabilities are recommended where market orientation capability theory recommends an outside-in view of a company.

Understanding customer requirements typically leads to market effectiveness; so, a market-oriented firm can utilise its resource capacity adequately (Stevenson, 2009; Vorhies and Morgan, 2005). A firm's market share growth, desired market position, and sales growth are notable indicators of its market effectiveness (Vorhies and Morgan, 2005; Vorhies et al., 2009). Market effectiveness is considered a performance outcome (Cao et al., 2019a; Goic et al., 2021). Utilising perceptual metrics of the firm's performance in terms of its market share, market position, and sales growth (e.g., Clark, 2000; Vorhies et al., 2009), we assessed its market effectiveness. While the existing research on information systems and operations management has examined the relationship between big data analytics capacity and firm performance (e.g., Akter et al., 2016; Mikalef et al., 2019), contemporary studies suggest that further research on customer/market-centric analytics capacity is required in order to achieve long-term sustainable performance (Rahman et al., 2021). Hence, the current study posits the following hypothesis:

H1. A sustained customer analytics capability positively impacts market effectiveness.

3.3. *Customer analytics capability and customer relationship performance*

Customer relationship performance may be influenced by a sustained customer analytics capability. Existing studies suggest that technological advancement empowers firms to connect with their customers more deeply than ever before (Coviello and Joseph, 2012; Zhang et al., 2020). Firms with an instrumental market orientation restore the relevant capabilities that expedite the connections between the customers' underlying needs and the firms' offerings (Alnawas and Hemsley-Brown, 2019). A market orientation capability accelerates through technological advancement support for relational information processing (Bhattarai et al., 2019; Na et al., 2019). A market orientation assists in generating firm-wide information, disseminates information and adequately responds to market intelligence in order to track the competitors' crucial moves and customers' needs (Bhuiyan et al., 2022). A market-oriented firm continuously searches for both exposed and unexposed desires of the customers (Guo et al., 2020); consequently, it must maintain an adequate operational capacity to satisfy the customers' known desires and reveal innovative solutions to address their underlying, inherent needs (Alnawas and Hemsley-Brown, 2019). This study forms a firm's sustained CAC framework, drawing on market orientation capability theory, which predicts higher customer relationship performance. The literature also indicates that a firm's superior relationship performance is generated by its capacity, which is untransferable, like resources, and has significant ramifications for creating and capturing value (Hossain et al., 2020; Ngo and O'Cass, 2012). The study therefore posits the following hypothesis:

H2. A sustained customer analytics capability positively influences customer relationship performance.

3.4. Customer relationship performance and market effectiveness

The extant literature on information management within operations suggests that a firm's market effectiveness (e.g., market share, profitability) improves, if it develops, maintains, and strengthens its customer relationships. It has been observed that customer relationship matrices, such as customer satisfaction and loyalty, are the core predictors of firms' performance measures (e.g., higher future sales growth) (Otto et al., 2020; Trainor et al., 2011). High levels of customer satisfaction lead to customer retention, which generates high revenues and a desirable market position through cross-selling, up-selling, and positive word-of-mouth (Behera et al., 2020). Satisfied customers generally stay with a particular firm; thus, lower costs are incurred due to the benefit of repeat purchases, that ensures the firm's effectiveness in the competitive market environment (Gupta and Ramachandran, 2021). In line with the previous research, we assume that maintaining customer relationships is vital for market existence. Thus, we posit the following hypothesis:

H3. Customer relationship performance positively influences market effectiveness.

The first hypothesis of this study (H1) assumes that sustained a customer analytics capability positively impacts market effectiveness; the second hypothesis (H2) assumes that a sustained customer analytics capability influences customer relationship performance; whereas the third hypothesis (H3) again assumes that customer relationship performance impacts market effectiveness. These assumptions show that a sustained customer analytics capability and market effectiveness have both direct and indirect influences; thus, customer relationship performance may mediate the relationship between a sustained customer analytics capability and market effectiveness. Therefore, we posit the following hypothesis:

H4. Customer relationship performance mediates the relationship between a sustained customer analytics capability and market effectiveness.

4. Research methods, sampling, and data analysis

The study's method is predominantly positivist quantitative in nature. Positivism is considered one of the epistemological aspects, similar to interpretivism research (Jones and Karsten, 2009; Orlikowski and Baroudi, 1991). The positivist research method encourages experiments, interviews, and surveys (Jones and Karsten, 2009; Weber, 2004). This method supports the Type IV theoretical taxonomy, which analyses data to explain the underlying facts and predict consequences empirically (Gregor, 2006). On the other hand, interpretivist methods are case studies, phenomenographic studies, and ethnographic studies (Sarker et al., 2013; Weber, 2004). Several researchers have noted that the distinction between positivism and interpretivism is not straightforward (Weber, 2004). Thus, the integration of these two methods is frequently recommended (Lee, 1991). Despite the predominant quantitative focus of this study, following the scholarly research guidelines (e.g., De Luca et al., 2020), the study also applied the qualitative method during the initial phases. The qualitative study employed a judgement sampling procedure (e.g., Zhu et al., 2020), while the quantitative study employed a random sampling procedure (e.g., Van Jaarsveld et al., 2019). A partial least square (PLS)-based structural equation modeling (SEM) technique was applied to validate the final higher-order research model, whereby all of the reliability, validity, and robustness methods were checked (Sarstedt et al., 2019).

4.1. Measurement scales confirmation

The survey measurement scales were adapted from previous, relevant, well-established studies; for example, customer value creation capability (CVCC) items were adapted from Mu (2015), Srinivasan et al. (2002), and Talke and Hultink (2010). Customer value delivery capability (CVDC) items were adapted from Lee et al. (2019) and Oh and Teo (2010). Customer value management capability (CVMC) items were adapted from Nam et al. (2019) and Wang et al. (2020). Customer relationship performance (CURP) items were adapted from Ngo and O'Cass (2012) and Trainor et al. (2011). The performance indicator was evaluated based on analytics managers' reports, who handle the customers' data and possess evidence regarding whether or not their customers are satisfied, and whether or not the firm can sustainably attract and retain customers as part of maintaining the relationship. Moreover, the articles that we chose for scale adaption also collected data from the firm/management level to assess the customer-relationship performance. Further, the market effectiveness (MREF) items were adapted from Vorhies et al. (2009). For the current study, the face validity of the survey instruments was confirmed by using a judgmental sampling technique involving 20 interviews with managers and academics (Nayak et al., 2021; Ou et al., 2017). In addition, 20 pre-tests were conducted to evaluate the question formulation and sentence structure using judgmental sampling, and 85 managers participated in the subsequent questionnaire pilot testing phase, using a random sampling strategy. These processes were crucial for confirming the functionality of the scale (De Luca et al., 2020). The study used seven-point Likert scales for the dependent and independent variables items. The scales ranged from (1) strongly disagree to (7) strongly agree for all of the variables, except for MREF. The MREF scales ranged from (1) much worse than the competitors to (7) much better than the competitors.

4.2. Main survey data

A sample of retail managers was selected, based on their proficiency regarding managing consumer data as part of their daily retail operations. To obtain a genuinely representative sample, a reputable research firm with access to a large database of retail managers was contracted. The survey questionnaire utilised screening questions to select appropriate respondents. Only 372 of the more than four thousand managers who attempted to complete the questionnaire using the research firm's database passed the screening questions and were therefore considered representative. Additionally, the study examined attention check questions, the survey completion time, and linear responses. Using a multivariate outliers technique, the data were refined, and normality was confirmed prior to the hypothesis testing (Marchant et al., 2018; Sullivan et al., 2021). Ultimately, the analysis was applied to data collected from two hundred and fifty-seven (257) respondents. According to Hair Jr et al. (2016, p. 48) "when the maximum number of independent variables in the measurement and structural models is five, one would need 45 observations to achieve a R^2 statistical power of 80% for detecting values of at least 0.25 (with a 95% confidence interval)". Considering the research model, our sample size of 257 is well above the threshold level.

According to the demographic data, a higher percentage of the respondents were male (55.3 %) compared to female respondents (43.2 %). A significant proportion of the respondents (40.1 %) were aged between 25 and 35 years-old. In terms of educational qualifications, the majority of the respondents had obtained a Bachelor's degree (41.2 %), and the next largest group possessed a Master's degree (30.0 %). Senior manager accounted for 26.1 % of the respondents' job titles, while business analyst made up 25.7 %. The data also reveal that 69.2 % of the respondents represented medium and large-sized organisations, as detailed in Table 2.

Table 2
Demographic profile of the respondents.

Items	Categories	%	Items	Categories	%
Gender	Male	55.3	Age	Less than 25 years	12.8
	Female	43.2		25 to <35 years	40.1
	Do not wish to disclose	1.6		35 to <45 years	21.8
				45 years or more	25.3
Education	Diploma certificate	20.2	Position	Senior manager	26.1
	Bachelor's degree	41.2		Head of insights & analytics	8.9
	Master's degree	30.0		Analytics manager	14.8
	Doctorate	3.5		Business analyst	25.7
	Other	5.1		Operations manager	13.2
				Other	11.3
Firm size	<20 employees (small)	30.7	Firm age	<10 years	42.8
	20–<200 employees (medium)	45.1		10–<20 years	37.0
	200 ≤ employees (large)	24.1		20 ≤ years	20.2

4.3. Addressing non-response bias

The study applied four steps to check the presence of non-response bias. First, the study addressed non-response bias by providing prospective respondents with a participant information sheet that outlined the study's academic purpose, together with the measures taken to protect the participants' confidentiality, and anonymity. Second, a Qualtrics version of the questionnaire was administered using the research firm's database. Respondents were unable to advance to the next question/page until they had responded to all of the existing questions on a page. Third, the study verified that all of the samples (i.e., managers of different sizes of retail firms) participated in the survey spontaneously, without any skewed responses from a specific branch (Maier et al., 2019). Finally, using the paired *t*-test technique, a random 25 % of the data were checked from the first and last half of the overall responses. The result did not reveal any statistically significant difference. This procedure ensured that this study was not affected by non-response bias.

4.4. Addressing common method variance (CMV)

The study applied both a priori and post-hoc methods to overcome the common method bias issues (Hulland et al., 2018). For example, the independent variable and dependent variable questions were separated during the data collection phase. The study applied different response scales for the outcome variable (e.g., MREF scales). The study contained a few questions that differed from the theoretical variables; namely, the marker variable. The analysis of the marker variable and original model variables provided non-significant co-relations, where $r = 0.017$, $p > 0.05$ for CVCC; $r = -0.002$, $p > 0.05$ for CVDC; $r = -0.032$, $p > 0.05$ for CVMC; $r = 0.010$, $p > 0.05$ for CURP; and $r = 0.047$, $p > 0.05$ for MREF with a marker variable.

4.5. Data analysis

The study employed Partial Least Squares (PLS)-based SEM (Structural Equation Modeling) for the data analysis. PLS is an appropriate choice when undertaking complex hierarchical model assessments (Chin, 2010). The study forms a higher-order sustained customer analytics capability using the first-order constructs items repeatedly, following the guideline suggested by previous studies (Becker et al., 2012). The first-order reflective constructs were considered mode A, and the second-order construct was considered mode B (Chin, 2010). The study also applied non-parametric bootstrapping, considering 5000 replications to identify the significant level and path coefficients between the constructs (Hair Jr et al., 2016). Moreover, testing the goodness-of-fit (GOF) is only beneficial for studies that adopt a confirmatory method, whereas PLS-SEM needs confirmation, explanation, and prediction consideration (Hair Jr et al., 2020). Therefore, the question arises of why such a standard for assessment based on a purely confirmatory perspective should be applied when it is not the central objective of analysis (Hair Jr et al., 2016). Thus, following other top-tier PLS-SEM-based studies, the current study conducted a confirmatory composite analysis (CCA) (Hubona et al., 2021). CCA includes an estimation of the loadings and significance, items reliability, construct reliability, average variance extracted (AVE), discriminant validity – HTMT, nomological validity, and predictive validity (Hair Jr et al., 2020). Further, in analysing the data, the study considered firm size (FRS), data analytics experience (DAE), age of firm (AOF), and the respondent's position (RSP) as the control variables, similar to other relevant studies (e.g., Cao et al., 2019b).

4.6. Measurement model

The study estimated nine (9) items for the second-order sustained CAC construct that originated in the first-order CVCC (3 items), CVDC (3 items), and CVMC (3 items) constructs. The findings show all of the first-order items of sustained CAC, and its outcome variable items loading exceeds 0.70, where the composite reliability (CR) values of the constructs are >0.80. The average variance extracted (AVE), which meets the threshold of >0.50, confirms the convergent validity (see Table 3). The variance inflation factor (VIF) of the variables shows that the range of 1.028 to 1.366 (≤5) indicates minimum collinearity. The square root of the AVEs in the diagonals are higher than the latent variables constructs correlation, which confirms the discriminant validity of the study (e.g., Cao et al., 2019b; Chen et al., 2014) (see Table 4). The HTMT value is smaller than 0.90, which also suggests that the constructs possess discriminant validity (Henseler et al., 2015). The findings also show that CVCC ($\beta = 0.411$), CVDC ($\beta = 0.225$), and CVMC ($\beta = 0.456$) are essential precursors of sustained CAC, which has established a more powerful R^2 value (0.991), as all of the lower-order constructs explain the higher-order CAC construct.

4.7. Structural model

The study estimates the path-coefficients (β), level of significance (*p*-value and t-statistics), coefficient of determination (R^2), and effect size (f^2), to test the hypothetical relationships. The findings show that the CAC-MREF association is important ($\beta = 0.264$, $p < 0.001$). Likewise, CAC-CURP ($\beta = 0.701$, $p < 0.001$) and CURP-MREF ($\beta = 0.607$, $p < 0.001$) are substantial. Thus, the effects show that hypotheses H1, H2, and H3 are supported. The analysis for this study evaluated the effects of the mediating variable using the methods of Hayes et al. (2011). The result supports the mediation linkage of CAC-CURP-MREF ($\beta = 0.425$, $p < 0.001$) (see Table 5). Therefore, H4 is supported. The analysis estimated an R^2 of 0.491 for CURP and 0.650 for MREF, demonstrating the acceptability of CAC as a significant variable (see Fig. 2). Overall, the results show appropriate, adequate effect sizes (f^2) of the theorised connections (Cohen, 1988).

4.8. Robustness tests

The study checked the predictive validity using the Stone-Geisser's Q^2, where the values of 0.329 for CURP and 0.399 for MREF confirm the results' adequacy (Chin, 2010). This study confirms the model's nomological validity using PLS-Predict, where 10 × 10 training and holdout samples generate and evaluate the predictions (Shmueli et al., 2019). The findings show that the Q2_predict results are >0, which confirms the model's superiority. PLS-based prediction yields more accurate out-of-sample predictions (e.g., more minor prediction errors) for

Table 3
Assessments of the measurement scales and control variables on the research model.

Reflective constructs	Items	Loadings	CR	AVE
Customer Value Creation Capability (CVCC)	*Customers' data-driven analytics empowers our firm's operations to:*		0.864	0.679
	CVCC1: Forecast trends appropriately before they are entirely noticeable.	0.845		
	CVCC2: Develop customised recommendations according to customers' preferences.	0.813		
	CVCC3: Perform offerings based on customers' needs.	0.814		
Customer Value Delivery Capability (CVDC)	*Customers' data-driven analytics enables our firm's operations to:*		0.889	0.728
	CVDC1: Maintain a consistent service process across all the channels (e.g., online, mobile, offline channels).	0.846		
	CVDC2: Present overall consistent information in multiple channels.	0.824		
	CVDC3: Support customer inquiries in multiple channels (e.g., online, mobile, offline channels).	0.888		
Customer Value Management Capability (CVMC)	*In the presence of customer-focused analytics, our advanced system enables our firm's operations to:*		0.876	0.703
	CVMC1: Utilise various tools to integrate customers' data from multiple sources.	0.831		
	CVMC2: Protect customers' personal information.	0.835		
	CVMC3: Ensure adequate security for customers.	0.849		
Customer Relationship Performance (CURP)	*Please rate your firm's customer-centric operational performance over the past three years in the following areas.*		0.901	0.694
	CURP1: Satisfying customers	0.823		
	CURP2: Sustainable relationship	0.858		
	CURP3: Attracting customers	0.829		
	CURP4: Retaining customers	0.822		
Market Effectiveness (MREF)	*Using customer-focused analytics, how well has your firm achieved its performance goals in terms of ________ in*		0.840	0.637
	the last three years relative to competitors?	0.844		
	MREF1: Sales growth	0.834		
	MREF2: Market share growth	0.710		
	MREF3: Desired Market Position			

	Items	Path Weights	t-statistics
Control Variables (COV)	Firm Size (FRS)	−0.039	0.983
	Data Analytics Experience (DAE)	0.028	0.617
	Age of Firm (AOF)	−0.023	0.476
	Respondent's Position (RSP)	−0.032	0.899

Table 4
Correlations and AVEs[a].

	CVCC	CURP	CVDC	MREF	CVMC	AOF	DAE	FRS	RSP
CVCC	0.824								
CURP	0.342	0.833							
CVDC	0.413	0.494	0.853						
MREF	0.391	0.483	0.381	0.798					
CVMC	0.438	0.341	0.454	0.321	0.838				
AOF	0.066	0.194	0.089	0.113	0.141	N/A			
DAE	0.098	0.093	0.061	0.081	0.012	0.401	N/A		
FRS	0.127	0.218	0.138	0.124	0.106	0.403	0.329	N/A	
RSP	−0.012	0.025	−0.026	−0.022	0.047	0.125	−0.042	0.066	N/A

[a] Square root of AVE on the diagonals.

Table 5
Results of the structural model.

Hypotheses	Main model	Path coefficients	Standard error	*t*-Statistic
H1	CAC – MREF	0.264	0.062	4.308
H2	CAC – CURP	0.701	0.050	13.90
H3	CURP – MREF	0.607	0.060	10.19
H4	CAC - CURP - MREF	0.425	0.050	8.555

the indicators of MREF. The model has a strong predictive power regarding MREF. The main theoretical proposed model provides a smaller BIC (Bayesian information criteria) value for MREF (−232.064), which is related to the revised model's MREF omission of CURP (−149.651), and confirms full support for the main theoretical research model (Hair et al., 2019). Further, an attempt was made to obtain objective data, as Hulland et al. (2018) suggest. This showed that the objective data results are significantly co-related with the subjective measures; for example, the sales growth percentage was confirmed by 145 of the 257 respondents. Their responses were co-related with their subjective data and the result was found to be significant ($r = 0.313$, where $p < 0.01$) (e.g., De Luca et al., 2020).

5. Findings and discussion

The data gathered from the 257 managers indicate that a customer value creation capability, customer value delivery capability, and customer value management capability are important antecedents for constructing a higher-order model of a sustained customer analytics capability. In addition, the findings demonstrate that a retail company's customer analytics capability exerts a substantial influence on the performance of its customer relationships and market effectiveness. The findings also reveal the role of customer relationship performance as a mediator between a sustained customer analytics capability and market effectiveness. Overall, a sustained customer analytics capability explains 49.1 % of the variance in the customer relationship performance and 65 % of that in market effectiveness. Table 3 reveals that none of the control variables are significant (e.g., firm size, data analytics experience, age of firm, and respondent's job position). Overall, the inclusion of control variables does not affect the estimations of the explanatory variables in a data-rich business environment. Consequently, the results of the model as a whole do not limit the effect of a sustained customer analytics

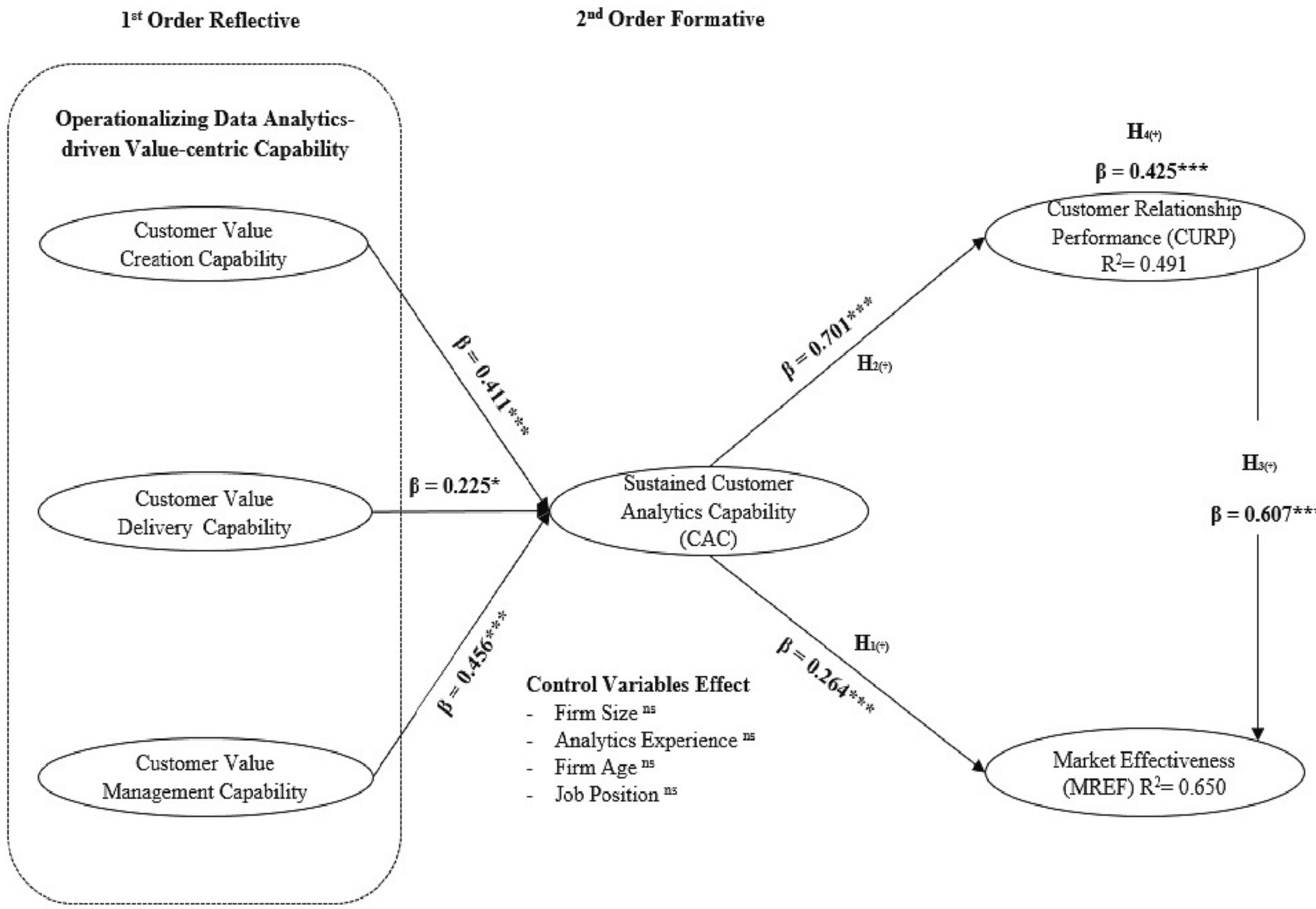

Fig. 2. Structural model.
$^{***}P < 0.001$, $^{**}P < 0.01$, $^{*}P < 0.05$, ^{ns} = not significant.

capability on market effectiveness.

The concept of digitisation within business operations involves the conversion of analog/manual processes into digital ones, which enables the rapid generation of a large volume of market data and functions as a source of recurring revenue (Ritter and Pedersen, 2020). Additionally, digitalisation optimises the internal processes and reduces the expenses. Nevertheless, the use of new technologies within digitalisation can also transform the overall business model and progressively expand the business operations. Therefore, the implementation of new technologies can have a profound impact on the business operations. According to digital technology specialists, the digital age has revolutionised the responsiveness of technology (Balci, 2021; Climent and Haftor, 2021). The effective adoption of digital technology occurs when businesses and organisations take advantage of the potential learning that accompanies operationalizing offerings, including both products and services (Llopis-Albert et al., 2021). This study highlights the importance of a sustained customer analytics capability within a firm's operations, which can create value for customers sustainably by addressing the current trends and utilising the offerings. Additionally, it emphasises the significance of value delivery and management with regard to multi-channel operationalizing data. This business activity is data analytics-driven, and environmentally-sustainable, ensuring zero carbon emissions. These data analytics-driven efforts within firms' operations generate sustainable market performance. In the digital era, all businesses must reduce their latency and increase their market environment awareness. As a result, numerous businesses are adopting and implementing cutting-edge technologies to attain a competitive advantage and achieve optimal performance (Akhtar et al., 2019). This study provides evidence that a capability regarding value creation, value delivery, and value management are the essential antecedents to a company's sustained customer analytics capability. Existing studies have acknowledged the importance of value generation but failed to emphasise firms' value-centric analytics capability (e.g., Itani et al., 2019; Keränen and Liozu, 2020; Parthiban et al., 2021). This research contributes to the existing body of knowledge by establishing that data-driven value creation, value delivery, and a value management capability serve as the core antecedents for establishing a sustained customer analytics capability within business operations that leverages market insights.

6. Conclusion and limitations

In conclusion, our research has made significant theoretical contributions that can be applied to managerial practice. We also acknowledge the limitations of our study and suggest potential avenues for future research to address these limitations and further advance the field. By working on these identified limitations, future research has the potential to enhance our understanding of the topic and provide actionable insights for practitioners.

6.1. Theoretical contributions and managerial implications

The study's findings shed new light on the market orientation capability theory within sustainable operation research. Our findings establish the distinct value proposition of a market orientation capability in the competitive retail business environment, that is dominated by big data. In the contemporary retail industry, consumer data are the key to success. Numerous organisations utilise analytics to examine customer data (Agile-analytics, 2019; Braun and Garriga, 2018).

However, the traditional RBV emphasises firm VRIN resources, that are insufficient to boost a company's performance. The company's perspective should be both market- and customer-centric (Rahman et al., 2021). In a data-rich environment, a company should acquire the ability to meet the market demand by satisfying the needs of its current customers. This study establishes a market orientation capability in order to generate a framework for a customer analytics capability with the aim of ensuring market success. Despite the fact that the concept of digital transformation has evolved in recent years (Vial, 2019), many companies can transform their businesses and substantially modify their organisations by employing digital technologies, particularly customer analytics. Despite the growing awareness of the potential of customer analytics to enhance an organisation's capability, conceptual and empirical research on the impact of customer analytics on sustainable operational digital transformation processes features infrequently in the literature, which is where this study makes its contribution. There are five major contributions by this study, including three theoretical and two managerial implications.

First, our findings support a market orientation capability for explaining a higher-order sustained customer analytics capability and predicting customer relationship performance together with market effectiveness. Theoretically, RBV focuses on a firm's inside-out activities; however, a firm should achieve a distinct position in order to meet the outside-in demand. From a market-oriented perspective, a firm's capability to equip itself with a distinct ability within the organisation is based on its ability to capture the scenario from the market and respond to the outside market demand.

Second, while the previous research has demonstrated the relationship between an analytics capability and firm performance (Calderon-Monge and Ribeiro-Soriano, 2023; Gupta et al., 2020; Ferreira et al., 2022; Mikalef et al., 2017), this study extends that knowledge to demonstrate how an analytics capability becomes effective in the market by enhancing customer relationship performance. While the existing research acknowledges the importance of customer relationship management in the business world (Chuang and Lin, 2013; Rapp et al., 2010; Verhoef et al., 2010), the research has failed to demonstrate the importance of customer relationship performance in mediating the relationship between an organisation's analytics capability and its overall market effectiveness. In this context, this study extends the knowledge by explaining the mediating effect of customer relationship performance.

Third, the research results make a significant contribution to a variety of established studies on business and information systems that seek to enhance the interdisciplinary research, as exemplified by Rust and Huang (2014) and Verhoef et al. (2021). Specifically, the theoretical framework of a market orientation capability introduces the concept of a sustained customer analytics capability as an integral component of big data information system management, business operations, and marketing studies. This contribution represents a substantial advance in the existing knowledge base regarding these fields.

Fourth, the managers of a retail company, for instance, should emphasise their ability to create value by anticipating the current trends, customising the recommendations, and offering products based on consumer segment requirements. Managers must maintain a capability to deliver value by maintaining a consistent service process, presenting consistent information, and facilitating customer enquiries across channels. Managers should also reconcile a value management capability by integrating customer data from multiple channels, safeguarding customers' personal information, and ensuring adequate customer security.

Finally, in practice, this research significantly contributes to the United Nations Sustainable Development Goal (SDG) number nine (9): industry, innovation, and infrastructure. The retail apocalypse is currently a major issue, where sustainable development is expected. Despite the advances in technology, analytics, and big data, firms are overwhelmed and are introducing advanced technology without a clear understanding of how to meet their customers' expectations. The study findings show that those retail firms that practice customer analytics capability antecedents are influential in the market. Accordingly, it is recommended that retail firms should prioritise the adoption of an innovative infrastructure in their operations in order to enhance their customer attraction, retention, and relationship-building efforts, and thereby increase the overall level of customer satisfaction. These measures are likely to result in sustained sales growth, an enhanced market positioning, and a rise in market share.

6.2. Limitations and avenues for future research

As with other research studies, the present research suffers from certain limitations that should be considered in future investigations. Firstly, the data collection process employed in this study was cross-sectional, which was necessary to test the theoretical framework. To obtain more precise and accurate results, however, future research might adopt a longitudinal approach. Secondly, the data used in this study were based primarily on subjective perceptions provided by the managers, and included some quasi-factual information. To improve the accuracy and objectivity of the data, future research could explore alternative methods of data collection that facilitate the collection of more objective and precise data. Thirdly, the present study solely examines a customer analytics capability through the lens of a market orientation capability, leaving scope for future research to explore a marketing analytics capability, AI capability, or retail analytics capability under the same market orientation capability framework. Fourthly, the study investigates the antecedents of a sustained customer analytics capability as the predictors of customer relationship performance and market effectiveness. Future research might consider testing other outcome variables such as market-responsive agility, customer centricity, and a sustained competitive advantage, not only within the retail industry but also across other sectors. Fifthly, previous studies have suggested that AI can enhance a firm's performance, and that market turbulence (including technological changes, diverse market events, and intense competition) can affect a firm's performance. No moderating effects within the market orientation capability theoretical paradigm were investigated, however, in the current study. Within this framework, future research could investigate the moderating effect of an AI orientation and market turbulence. Overall, the study identifies possible future research avenues in the disciplines of business operations and information systems.

CRediT authorship contribution statement

Md Afnan Hossain: Conceptualisation, Methodology. Shahriar Akter: Funding acquisition, Formal analysis. Venkata Yanamandram: Review the draft manuscript. Samuel Fosso Wamba: Supervising the entire project, Proofread.

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