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The influence of quality of big data marketing analytics on marketing capabilities: the impact of perceived market performance!

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Received 5 July 2023
Revised 1 September 2023
26 November 2023
Accepted 18 December 2023

Abstract

Purpose – Big data marketing analytics (BDMA) has been discovered to be a key contributing factor to developing necessary marketing capabilities. This research aims to investigate the impact of the technology and information quality of BDMA on the critical marketing capabilities by differentiating between firms with low and high perceived market performance.

Design/methodology/approach – The responses were collected from marketing professionals familiar with BDMA in North America ($N = 236$). The analysis was done with partial least squares-structural equation modelling (PLS-SEM).

Findings – The results indicated positive and significant relationships between the information and technology quality as exogenous constructs and the endogenous constructs of the marketing capabilities of marketing planning, implementation and customer relationship management (CRM) with mainly moderate effect sizes. Differences in the path coefficients in the structural model were detected between firms with low and high perceived market performance.

Originality/value – This research indicates the critical role of technology and information quality in developing marketing capabilities. The study discovered heterogeneity in the sample population when using the low and high perceived market performance as the source of potential heterogeneity, the presence of which would likely cause a threat to the validity of the results in case heterogeneity is not considered. Thus, this research builds on previous research by considering this issue.

Keywords Big data marketing analytics, Marketing capabilities, Resource-based theory (RBV), Static and dynamic capabilities, Technology quality, Information quality

Paper type Research paper

Introduction

"Information is the oil of the 21st century, and analytics is the combustion engine," indicated previous Gartner Group director Peter Sondergaard in 2011 (Mavuduru, 2020). It has been forecasted that the big data analytics (BDA) market is set to reach $103 billion by 2023 (TechJury, 2022). Consequently, data is driving progress in new skill and capability development to enable data-driven decision-making in dynamic marketing environments.

Marketing analytics is accessing, storing and exploring market information (SAS, 2022) and deals with relatively small data sets, usually in a numeric structured format with limited analytic platforms and implementation capacity (Xu *et al.*, 2016). In the marketing context, changing consumer behaviour requires more careful identification of the target customers and an understanding of the more subtle buying patterns of customers (Nadler and McGuigan, 2018). Big data (BD) refers to large, fast and complex data which is difficult to process using conventional analytical methods (Johnson *et al.*, 2019). Drawing on this, big data marketing analytics (BDMA) can be defined as accessing, storing and exploring market information with extensive data sets in various formats originating from multiple sources and is based on the collaborative effect of the analysis with advanced technological analysis

Marketing Intelligence & Planning

0263-4503
DOI 10.1108/MIP-07-2023-0319

tools and platforms as well as good quality information resulting in timely marketing insights. There are multiple points of differentiation in this definition in comparison to the definition of traditional marketing analytics. Without going through the obvious ones (i.e. the volume of data, data formats, plentitude of data sources, etc.), the researchers want to highlight the information quality and technology quality, which *jointly* form a commanding foundation of the BDMA.

BDMA can discover novel consumer interests and needs and identify relevant new opportunities. BD consists of the 5 V's (**V**olume, **V**alue, **V**eracity, **V**ariety and **V**elocity). The volume of the BD refers to the size and amount of the data, while the value stems from the discovery of valuable insights from the BD (Wamba *et al.*, 2017). To illustrate the volume aspect, BD growth statistics unveil that data formation will be over 180 zettabytes (10^{21}) by 2025 and that Google receives more than 3.5 billion searches daily (TechJury, 2022). Variety relates to the diversity of the various data types (structured, semi-structured, unstructured and raw). Velocity refers to the speed at which organizations receive, store and manage new data and the speed with which they process that data. Finally, veracity is related to the accuracy of the data (Teradata, 2022). Recent research has pointed out that 80–90% of the data generated nowadays is unstructured. Therefore, it is unsurprising that 95% of firms mention managing unstructured data as a problem (TechJury, 2022).

One of the many benefits that BD introduces for marketing is the enhanced knowledge of customers and how they evolve in their needs and preferences, and one of those is the ability to adapt to those needs and preferences. The marketing benefits of BD include better target marketing, insights, client-based segmentation and the recognition of sales and market opportunities (Tykheev, 2018).

A review of extant research reveals a growing interest in the intersection of marketing and BD. A text mining and topic modelling-based literature review paper examined the relevant research topics in BD and marketing (Amado *et al.*, 2018). The results reveal the common marketing topics like "market," "media," "product," "price," "consumer," "brand," etc., as well as technology-related terms like "algorithm," "Big Data," "architecture," "visualization," and "machine learning" etc. The unanticipated finding was that none of the previous research topics dealt with marketing research, technology and information quality nor with marketing capabilities development (e.g. marketing planning, marketing implementation and CRM). This is startling as the plentitude of previous research has discovered a significant relationship between marketing capabilities and a firm's financial performance (Erevelles *et al.*, 2016; Ji-fan Ren *et al.*, 2017; Kamboj *et al.*, 2015; Nath *et al.*, 2010; Vorhies and Morgan, 2005). Against this, research about technology and information quality as the antecedents of marketing capabilities seems worthwhile in the BD context.

Further, prior research has conceptualized the role of information quality in developing tangible and intangible assets and their role in developing marketing capabilities, however, without empirical verification (Foroudi *et al.*, 2017). Previous research has also examined the linkages between marketing analytics use, CRM and market performance. Again, the relationship between performance and CRM was verified, as well as the connection between marketing analytics use and CRM (Cao and Tian, 2020). It is notable, however, that the fundamental construct in the research by Cao and Tian was the use of *marketing analytics* and not the quality of the marketing analytics, which is potentially an essential subsequent construct in developing marketing capabilities. Thus, it appears that the role of information and technology quality in developing marketing capabilities remains primarily an unexplored research domain. Therefore, this research aims to fill this void.

Against this backdrop, the purpose of this research is to examine the impact of the quality of BDMA (as measured with technology and information quality) on marketing capabilities (marketing planning capability, marketing implementation capability and customer relationship management (CRM)) and whether the perceptions differ between companies with high and low perceived market performance on the premise that better marketing planning, and implementation and CRM capabilities should ultimately lead to better market performance. The objectives of this paper are to discuss the key constructs and their measurement variables and the relationships between the key constructs, introduce the analytical methodology and discuss the results and their academic and practical implications in the marketing context.

Literature review

Big data and marketing

BD has emerged as a critical component in manufacturing, retail, healthcare, oil and gas, telecommunications and financial services. In manufacturing, firms can improve operational efficiency and streamline business processes using BD. In retail, firms can create better product predictions, forecast demand and enhance in-store customer experiences, thereby improving customer lifetime value (CLV). In healthcare, hospitals can discover trends and threats in patterns by using predictive models. In oil and gas, companies can use data sensors to examine the performance of oil wells, equipment and drilling operations. Telecommunications companies can detect customer demands for new digital services and, at the same time, manage the constantly growing volume of data. Financial institutions can identify new market opportunities and lower fraud using BD (Desouza and Jacob, 2017; Oracle, 2022). The research in the different business disciplines regarding BD has experienced tremendous growth; however, this is surprisingly not the case in the marketing sphere (Amado *et al.*, 2018; Rejeb *et al.*, 2020).

In marketing, BD exists in various forms like clickstreams, audio and video, financial transactions and other marketing activities (Sun and Jeyaraj, 2013). In marketing, BD originates from real-time data, non-traditional forms of media and technology-driven and social media data (Schroeder, 2016). BD has evolved as a new marketing opportunity by creating competitive advantages and developing novel marketing prospects (Wamba *et al.*, 2019). Not surprisingly, the literature identifies “Big Data” not only as “the next management revolution” (McAfee *et al.*, 2012) but also as “the new raw material for business” (The Economist, 2010), or “the new science that holds the answers” (Gelsinger, 2012). By and large, the benefits of BDMA include a better understanding of markets and customers, enhanced productivity and profitability, and improved marketing performance measurement mechanisms (LaValle *et al.*, 2011). The benefits of BDA in marketing include detecting new customer segments, market opportunities, enhanced rewards, products and services for existing and new customers, more effective promotional campaigns, and measurement of campaign results (Vickery, 2016).

BDMA transforms data into eloquent marketing insights (Wixom *et al.*, 2013), enhancing profitability (Wamba *et al.*, 2019). Furthermore, quality data-driven decisions have been asserted to improve productivity by 1–3% (Junqué de Fortuny *et al.*, 2013) and enhance market share. Also, companies using BDMA were twice as likely to be in their industry’s top 25% for profitability and five times more likely to make more agile decisions than their competitors (Feliu, 2022). Furthermore, by being proactive, firms can adjust to the changing market conditions by conducting market research using BDMA (Sponder and Khan, 2018). To support these points, recent research has claimed that Netflix, for example, saves $1 billion annually on customer retention using BD (TechJury, 2022).

Perceived market performance

In this study, a construct being examined is what is referred to as the perceived market performance, which can be defined as the firm’s success in entering new markets and delivering new products and services to the market. The literature suggests that market performance will likely improve when Information Technology (IT) support for competitive strategy is high (Wang *et al.*, 2012). IT support for developing corporate assets like organizational, technological and marketing capabilities is crucial (Rivard *et al.*, 2006). Similarly, if BDA can provide valuable insights for marketing, the market performance should improve. Previous research has claimed that in highly competitive markets, market information quality is necessary to determine efficient means to interrelate with customers and consequently becomes an essential resource in building marketing interaction capabilities (e.g. CRM) with customers (Al-Zyadat and Al-Zyadat, 2018). Similarly, market information (enabled by technology quality in the context of BD) can be perceived as a critical ingredient for marketing planning and implementation (Maltz and Kohli, 1996). Also, previous research has expectedly established a positive relationship between marketing planning (Pulendran *et al.*, 2003), marketing implementation (Lagat and Frankwick, 2017) and CRM (Ernst *et al.*, 2011) and business performance, which is crucial in the context of this research.

It is to be noted that this research does not hypothesize any impact of perceived market performance on the constructs under investigation; instead, the perceived market performance will be utilized as a categorical construct between low and high perceived market performance.

Information quality

The theory of information, as established by Shannon (1948), claims that the fundamental premise of information is the need for production at one point and reproduction at another matter, and this has led to technologies (like BDA) that encode, transmit, decode and stock information (Omoregie, 2021). In the context of BDMA, the meaning of information quality becomes crucial as BDMA is expected to bring valuable marketing insights for decision-makers. To stress the significance of data quality, recent research has indicated that meagre data quality costs the US economy roughly $3.1 trillion yearly (TechJury, 2022).

Information quality is the outcome of processing relevant information and can be derived from various types of records, reports, books, databases, the internet and library catalogues (Tseng, 2017). Some researchers have claimed information quality to be multidimensional and defined it by the quality of its components, including quality of goal definition, data quality, analysis quality and quality of utility measure, and the relationships between them (Kenett and Shmueli, 2014). Other researchers have indicated that information quality has the following dimensions: accuracy, comprehensiveness, currency, reliability and validity (Taylor, 1986). More recent research has claimed that using a contingency approach in the definition of information quality depends on the context and is therefore comprised of tradeoffs. Consequently, a uniform definition of information quality is difficult to accomplish (McNab and Ladd, 2014).

In the context of this research, information quality is expressed by the currency, accuracy, format and completeness of data (Akter *et al.*, 2016). Currency refers to the information being recent; accuracy denotes the correctness of the data; format signifies the information enabling users to read and understand easily; and completeness describes the wholeness of the data (Setia *et al.*, 2013).

Technology quality

The resource-based view (RBV) intends to detect the resources and capabilities that allow a firm to achieve a level of performance that the competition cannot easily equal. Prior RBV research has underlined that resources as such cannot be beneficial unless they enable the firm to create distinctive choices or to implement unique marketing strategies (Lioukas *et al.*, 2016). Against this theoretical underpinning, technology can be a crucial resource for firms and contribute to sustained competitive advantage. However, technology, specifically information technology, alone cannot achieve such a goal. Instead, the firms' rare resources and capabilities form the basis for cultivating a sustainable competitive advantage through long-term customer relationships (Reyes-Mercado, 2021).

Technology quality can be outlined as the user-perceived quality where adaptability, integration, privacy, response time and system reliability are essential (Davenport, 2013). The BDA should adapt to various user needs (Wamba *et al.*, 2018). For example, previous research has shown that 90% of Internet users nowadays use their mobile devices for browsing. Therefore, the system must capture these aspects of technology behaviour (Leivesley, 2021).

System integration consists of different components or systems linked together as one unit. System integration combines divergent and sometimes incompatible data and communication systems into uniform information technology architecture. Integration solutions reveal current information assets in the information systems and allot them to several marketing applications and processes (Myerson, 2001).

The ability to prevent information from being known to people other than those to whom the information is given is referred to as information privacy. The transmission of personal information over the internet can cause serious privacy issues (Jain *et al.*, 2016). Privacy issues related to BD can arise during the data collection, from data generation to data storage and processing. By restricting access to data, the danger of privacy infringement during data production can be reduced (Jain *et al.*, 2016). As more and more decisions are based on data, the reliability of the data becomes imperative. The managers make strategic and operational decisions by analyzing data in large quantities in real-time (Newell and Marabelli, 2015).

Extant research has pointed out that the technology quality in data warehousing positively affects decision-making, which means that a flexible data system can adapt quickly to changes in user needs and produce relevant, up-to-date and high-quality information (Gorla *et al.*, 2010).

Marketing capabilities

Consistently with the RBV, previous research has defined marketing capabilities as "the integrative process of utilizing firm resources (tangible and intangible) to recognize the specific needs of consumers, achieve competitive product differentiation and realize superior brand equity" (Day, 1994). Extant research has recognized marketing capabilities as a critical construct firms use to achieve competitive advantage (Kamboj *et al.*, 2015; Najafi-Tavani *et al.*, 2016).

It is essential to distinguish between resources and capabilities when discussing the concept of capabilities and their development. Many firms can access commonly available resources. Still, the unique capabilities enable the firms to arrange and implement the resources and subsequently generate distinctive products and services. Accordingly, this leads to the differentiation of the products and services and creates a solid foundation for competitive advantage and heterogeneity among the firms in the marketplace (Bitar and Hafsi, 2007).

Marketing capabilities are the link between the firm and its customers and the skill to satisfy customers. Therefore, having good quality and current market information created by excellent current technology is critical in the context of BD when using current market information to enhance customer satisfaction, revenue and the firm's profitability (Ahmed *et al.*, 2014).

Recent research distinguishes between resource-based, static and dynamic capabilities. Based on the RBV, the assumption is that the reason for heterogeneity between the firms stems from access to strategic resources. The static marketing capabilities provide a subliminally static description of the organizational capabilities, which are well-developed and challenging to replicate procedures that enable the performance of conventional marketing processes (Day, 2011). When the attention is on utilizing current internal resources instead of monitoring the environmental changes, it may cause even large established companies to fail, as Christensen (2000) has explained. Examples of static marketing capabilities include the traditional marketing mix elements like advertising, channel management, marketing communications, selling, pricing, marketing planning and implementation (Guo *et al.*, 2018).

On the other hand, dynamic capabilities are cross-functional business processes that enable firms to create value for customers responsively and efficiently. These include capabilities like market sensing, brand management and CRM, which have been discovered to be connected to the profit growth of firms (Cao and Tian, 2020; Morgan *et al.*, 2009a, b). In the case of this research, the decision was made to concentrate on the more advanced and forward-looking marketing capabilities (i.e. marketing planning, implementation and CRM) instead of the more elementary and short-term marketing capabilities (e.g. advertising, promotion, channel management, pricing, etc.)

Hypotheses development

BD's technology and information quality are essential to marketing decision-making (Aliahmadi *et al.*, 2022; Li, 2021). Thus, information and technology quality are valuable for marketers when developing marketing capabilities (Barton and Court, 2012). Previous research has established the connection between quality analytics, business value and firm performance (Erevelles *et al.*, 2016; Ji-fan Ren *et al.*, 2017; Kamboj *et al.*, 2015; LaValle *et al.*, 2011).

For marketing capabilities to be effective, information quality is crucial, as it allows marketers to predict, plan, make better marketing decisions, implement and manage those decisions, and meet customers' needs more effectively. Extant research has indicated a mediating role of operational capabilities between information quality and corporate performance (Tseng, 2017) and the quality of information technology in developing management capabilities (Alolayyan *et al.*, 2022). Furthermore, previous research compared the IT leaders according to Information week to a control group examining the relationship between information system resources and firm performance. The results indicated that firms with high IT capabilities outperformed the control group (Bharadwaj, 2000; Rivard *et al.*, 2006). These results were later confirmed with the research performed by Santhanam and Hartono (2003). Consequently, based on the theoretical foundation of the theory of information and RBV, the following hypotheses are set:

H1. The information quality in the context of BDMA is significantly and positively related to a firm's marketing planning capabilities.

a. When the perceived market performance is low.

b. When the perceived market performance is high.

H2. The technology quality in the context of BDMA is significantly and positively related to a firm's marketing planning capabilities.

a. When the perceived market performance is low.

b. When the perceived market performance is high.

Further to the vital marketing planning capabilities, allocating and configuring marketing resources based on quality information and technology are required for proficiently implementing marketing programs, converting marketing strategies into actionable programs and quickly executing marketing strategies (Cao *et al.*, 2021). Previous research has indicated that a firm's capability to investigate and appreciate market conditions delivers invaluable insights and thus enables it to allocate and implement its marketing resources, including media spend, brand management and serving existing and new customers (Foley and Fahy, 2009). Based on the theoretical foundation of the theory of information and RBV and the previous research findings (Bharadwaj, 2000; Rivard *et al.*, 2006), the following hypotheses are set:

H3. The information quality in the context of BDMA is significantly and positively related to a firm's marketing implementation capabilities.

a. When the perceived market performance is low.

b. When the perceived market performance is high.

H4. The technology quality in the context of BDMA is significantly and positively related to a firm's marketing implementation capabilities.

a. When the perceived market performance is low.

b. When the perceived market performance is high.

CRM is a customer-linking capability. It is the collection of practices, strategies and technologies that can be used to manage and analyze customer interactions with the firm and data throughout the customer lifecycle. The objective is to enhance customer relationships, customer retention and sales growth (Cao and Tian, 2020; Chai, 2020) and customer relationship performance (Chuanga and Lin, 2013). Firms that collect marketing knowledge from BDMA in a coordinated fashion are better positioned to optimize their CRM for prospective customers (Oztekin, 2018). CRM and BDMA jointly help firms better comprehend their customer base by profiling and modifying their marketing strategies, target marketing and budgets (Kunz *et al.*, 2017). The enhanced marketing capabilities enable better value creation by better understanding the customer base and the role of information and technology quality in building customer orientation and customer relationship capabilities (Setia *et al.*, 2013).

Through better information and technology quality, BDA helps make better CRM strategies, including customization of sales processes, personalization of services, customer interactions (Sharma, 2020) and service performance (Hsieh *et al.*, 2011). Based on the theoretical foundation of the theory of information and RBV and previous research (Bharadwaj, 2000; Rivard *et al.*, 2006), the following hypotheses are set:

H5. The technology quality in the context of BDMA is significantly and positively related to a firm's CRM capabilities.

a. When the perceived market performance is low.

b. When the perceived market performance is high.

H6. The technology quality in the context of BDMA is significantly and positively related to a firm's CRM capabilities.

a. When the perceived market performance is low.

b. When the perceived market performance is high.

Methodology

Sample and respondent characteristics

Responses were gathered among the marketing professionals with experience in BDMA via the SurveyMonkey marketing research company. The survey was conducted over about one week in Winter 2021, and over 970 responses were collected from Canadians and Americans whose ages were at least 18 at the time of the survey. There was financial compensation for the respondents for their time, which aligns with SurveyMonkey's policies. We initiated an

Internet-based questionnaire by posing a qualification question this initial question aimed to determine the participants' eligibility for the study. Therefore, the sampling method can be called purposive sampling, which is appropriate when some respondents are essential to the sample (Robinson, 2014).

Once eligibility was established, participants were directed to the main questionnaire. The requirement was that the companies where the respondents were working were at least in the limited deployment stage regarding BDMA (i.e. Stage 5 or later in Table 1). The final sample included 236 acceptable responses in various advanced stages of the active BDMA deployment (Murphy and Cox, 2016).

We utilized Cochran's formula (1977) for continuous data to determine the adequacy of the sample size. Our alpha level was set at 0.025 in each tail of 1.96, with an estimated standard deviation on a 5-point scale of 0.8 and an acceptable margin of error of 0.15. We calculated that a sample size of 137 was required based on these parameters. To consider the adequacy of the sample size for the use of partial least squares-structural equation modelling (PLS-SEM), extant literature has specified that if the minimum path coefficient is 0.11 and the required significance level is 5%, then a sample size of 155 is needed (Hair *et al.*, 2022). As the sample consists of 236 responses, an adequate sample size was reached based on both criteria.

Measurement and questionnaire development

We developed a questionnaire to gather data on critical constructs and their indicator variables. The items used in the questionnaire were adapted from existing literature (Appendix).

Structural model

Consistent with previous research (Akter *et al.*, 2017), the following model was developed based on the literature review (Figure 1). This model visually represents the hypotheses formulated for the current study. As mentioned earlier, the perceived market performance construct is not directly present in the structural model. It is used as a grouping construct to divide the responses into low and high perceived market performance responses to compare the structural model's low and high market performance responses.

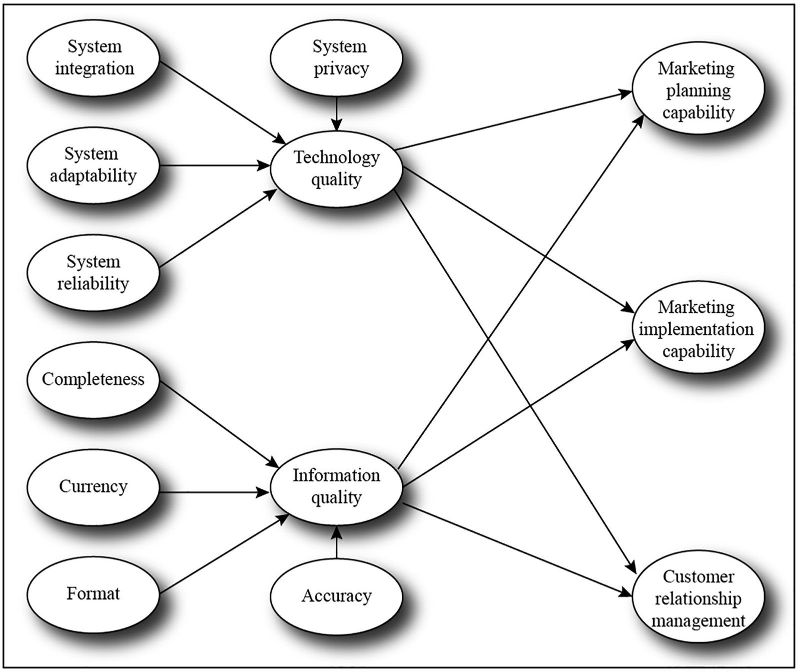
Method of statistical analysis

PLS-SEM was used as the statistical analysis method. There are two different methods of SEM: covariance-based (CB-SEM) and PLS-SEM. Hair *et al.* (2018) noted that these methods differ in their measurement idea and objective (i.e. common variance). Specifically, CB

Table 1. BDMA deployment stage in the respondents' companies

#	How do you rate the deployment of marketing analytics applications in your firm?	*N* (970)	%	*N* (236)
	Did not complete all questions in the survey	734	75.7	
1	Unaware of any marketing analytics applications			
2	Aware of the marketing analytics applications			
3	Knowledge of the marketing analytics applications but have not yet evaluated any			
4	Evaluation of the potential of the marketing analytics applications			
5	Limited deployment of the marketing analytics applications	62	6.4	26.4%
6	General deployment indicating wide impact on critical business processes	90	9.3	38.1%
7	Mature deployment for a longer period of time with legacy support	84	8.6	35.6%

Source(s): Created by the authors



Source(s): Created by the authors

Figure 1.
The structural model for the study

methods share variance in a variable with other variables. At the same time, PLS-SEM uses the total variance of indicator variables to generate linear combinations that represent relevant constructs. It is essential to understand these differences, as they can impact the results of data analysis and the conclusions drawn from it. By carefully considering each method's measurement idea and objective, researchers can choose the most appropriate approach for their research question and data set.

The decision was made to use PLS-SEM as the objective is predicting the critical target (endogenous) constructs and identifying key driver (exogenous) constructs as well as the fact that the goal of the research is not related to theory testing or confirmation (Hair *et al.*, 2022). Up-to-date suggestions for the assessment of the quality of both the measurement (outer) and structural (inner) models in PLS-SEM were followed (Ringle *et al.*, 2018).

Consistently with previous research (Akter *et al.*, 2017; Davenport *et al.*, 2012; McAfee and Brynjolfsson, 2012), and as the structural model is quite complex (Hair *et al.*, 2018), higher-order constructs for technology and information quality were utilized (Figure 1). Using higher-order constructs facilitates modelling constructs on a more abstract level than their more concrete low-order measurement dimensions. This can direct to a more efficient and effective modelling process. However, it is essential to note that prior research has also specified that using higher-order constructs can diminish the path model relationships and contribute to parsimony. Therefore, the two exogenous constructs under scrutiny in this research, information and technology quality, were handled separately, contributing to the marketing capabilities as it is feasible that their effect on the marketing capabilities constructs may differ. When using this method, it is essential to conceptualize and define the higher-order constructs using rigorous measurement theory (Sarstedt *et al.*, 2019). The model assessment can be done using either the repeated indicators or the two-stage approach in the reflective-formative approach, both of which yield practically similar results when the sample size is large enough (Sarstedt *et al.*, 2019). The selected method was the two-stage indicators approach, as the model contains a formative hierarchical latent construct model in an endogenous position (Becker *et al.*, 2012).

Consequently, the variance of the higher-order construct will be entirely explained by the lower-order measurement variables, i.e. the R^2 will be 1. Therefore, the latent variable score estimates must be added to the dataset instead of trying to estimate the model estimates. Then, in the subsequent analysis, these scores will be used as indicators in the higher-order construct measurement model (Sarstedt *et al.*, 2019).

Data analysis

Background data

Table 2 describes the sample populations of this research. The respondents represented a variety of industry types, including finance and insurance, information and cultural industries, education services, manufacturing, construction and real estate, among others. Correlations between the latent constructs and indicator variables can be seen separately for the first-order and second-order constructs in Appendix, respectively.

Assessment of the measurement model

The first step is to assess the individual scales used to measure the constructs. The assessment of the measurement model starts with the evaluation of the indicator reliability. A bias-corrected and accelerated bootstrapping analysis was done to determine the significance of the indicator variables. All indicator variable loadings were greater than 0.70 and significant to their relevant construct (Rosenbusch *et al.*, 2018).

The next step is the assessment of internal consistency reliability (Appendix). It is important to note that Cronbach's alpha is a conservative measure of reliability. In contrast,

#		*N* (%)	#		*N* (%)
	Country of residence			*Education*	
1	Canada	34 (14.5%)	1	High school or less	28 (11.8%)
2	United States	199 (84.3%)	2	Some college – no degree	23 (9.7%)
3	Other	3 (1.2%)	3	College diploma	25 (10.6%)
	Age group		4	Associate's	20 (8.5%)
1	19–24	55 (23.3%)	5	Bachelor's	70 (29.7%)
2	25–28	34 (14.4%)	6	Master's	45 (19.1%)
3	29–34	55 (23.3%)	7	Doctorate	21 (8.9%)
4	35–40	36 15.3%)	8	Other	4 (1.7%)
5	41–45	18 (7.6%)		*Years with the firm*	
6	46–54	14 (5.9%)	1	Less than year	15 (6.4%)
7	55–64	17 (7.2%)	2	2–5 years	73 (30.9%)
8	+65	7 (3.0%)	3	6–10 years	77 (32.6%)
	Years with the organization		4	11–15 years	39 (16.5%)
1	Less than year	15 (6.4%)	5	16–19 years	11 (4.7%)
2	2–5 years	73 (30.9%)	6	Over 20 years	21 (8.9%)
3	6–10 years	77 (32.6%)			
4	11–15 years	39 (16.5%)			
5	16–19 years	11 (4.7%)			
6	Over 20 years	21 (8.9%)			

Source(s): Created by the authors

Table 2.
Description of the sample ($N = 236$)

the composite reliability (target range 0.70–0.95) overrates the internal consistency reliability. Thus, the true reliability is between these criteria, where Cronbach's Alpha value is the lower and composite reliability is the upper bound (Hair *et al.*, 2022). On this basis, the internal consistency reliability can be considered acceptable. In terms of convergent validity, which is usually assessed with the average variance extracted (AVE) values the accepted threshold level of 0.50 was exceeded (see Appendix).

The next step is the assessment of discriminant validity, which indicates the extent to which a construct differs from other constructs (Hair *et al.*, 2022). However, this cannot be done using the usual procedure in the higher-order model's case due to repeated indicators. Extant research has indicated a need to assess the higher-order component as part of the structural model regarding the discriminant validity only.

Literature suggests the Heterotrait-Monotrait (HTMT) of the correlations for the assessment of discriminant validity, which signifies the ratio of the between-trait correlations to the within-trait correlations (Hair *et al.*, 2022). Research has suggested that the threshold value of 0.90 should not be exceeded (Henseler *et al.*, 2015). The HTMT analysis of correlations should serve as the basis for the discriminant validity test. As PLS-SEM does not rely on distributional assumptions, standard significance tests cannot be used to assess whether the HTMT correlation is significantly different from the value of one, and thus, significance is tested with the bootstrapping procedure (Hair *et al.*, 2022). If the bootstrap confidence interval includes 1, it indicates a lack of discriminant validity (see Table 3).

Research has advocated using a full collinearity test as a variance-based SEM equivalent to the common method bias (CMB) test (Lindell and Whitney, 2001). Consequently, the full collinearity appraisal was done as it may influence the measurement and structural model evaluation. The full collinearity appraisal includes both the vertical and lateral collinearity appraisal, which in this case was completed with the approach described by Kock and Lynn (2012) and Johnson *et al.* (2011). This can be done by inserting a random construct into the data set and creating a different model where all latent constructs are associated with the random dummy construct, which is computed with a variable with values between 0 and 1, and then executing the PLS-SEM scrutiny and examining the variance inflation factors (VIFs). The results indicated the lack of collinearity, as the variance inflation factor (VIF) values were close to 3 or lower both in the measurement and structural models (Hair *et al.*, 2022; Ringle *et al.*, 2018). Accordingly, there was no CMB in the dataset.

Assessment of the structural model

The assessment of the structural model starts with the appraisal of collinearity, which indicates the correlation between the exogenous predictors in the model. Collinearity is usually assessed with the VIF. All VIF values in the structural model were close to 3 or lower, indicating a lack of collinearity (Hair *et al.*, 2011).

		5% bias-corrected confidence interval	
Relationship	HTMT	2.5%	97.5%
Information quality → CRM	0.483	0.303	0.689
Information quality → Marketing implementation capability	0.580	0.369	0.779
Information quality → Marketing planning capability	0.529	0.302	0.739
Technology quality → CRM	0.375	0.143	0.559
Technology quality → Marketing implementation capability	0.247	0.031	0.451
Technology quality → Marketing planning capability	0.337	0.113	0.573

Source(s): Created by the authors

Table 3.
The assessment of discriminant validity with the Heterotrait-Monotrait correlations with bootstrapping significance

The predictive validity of the structural model is usually done with the R^2 and Stone and Geisser Q^2 values (Geisser, 1974; Stone, 1974) (Table 4). Extant research has established that R^2 values of 0.75, 0.50 and 0.25 can be called substantial, moderate, and weak, respectively (Hair *et al.*, 2022). Recent research has also recognized strength criteria for the Stone-Geisser Q^2 values, so values larger than 0.25 and 0.50 characterize medium and large predictive relevance (Hair *et al.*, 2020). On this basis, it can be claimed that there is a close to substantial predictive relevance and strength for the endogenous constructs.

Testing of hypotheses

Estimating the path coefficients is the last step in assessing the structural model and coincides with the hypotheses testing (Table 5, Figure 2). Extant research has indicated that statistical significance is insufficient when reporting the results and that effect size should also be noted (Cohen, 1992; Kline, 2004). The effect size may be the most critical finding in the statistical analysis as, with a sufficiently large sample size, statistical testing can find significant differences that are meaningless in practice. For that reason, the reporting of the *p*-values is insufficient (Sullivan and Feinn, 2012). The effect size is not influenced by sample size; therefore, it is comparable across different research studies (Hair *et al.*, 2010). Previous literature has denoted that the values of 0.02, 0.15 and 0.35 indicate the exogenous constructs have small, medium or large effect sizes, respectively (Hair *et al.*, 2022).

Table 4.
Explanatory power and predictive strength

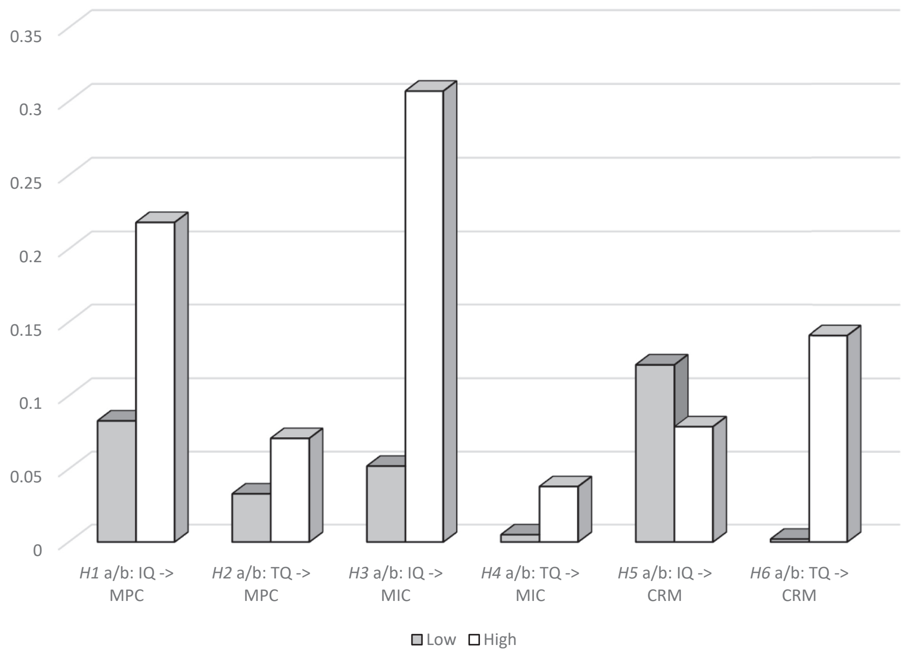
Construct	R^2	R^2 adjusted	Q^2
Customer relationship management (CRM)	0.70	0.70	0.69
Marketing implementation capability	0.66	0.66	0.65
Marketing planning capability	0.72	0.72	0.71

Source(s): Created by the authors

Table 5.
The significance of the path coefficients

#	Exogenous construct	Path coefficient	*p*-value	Hypotheses support	Effect size (f^2)	Effect size description
1a/b	Information quality (IQ) → Marketing planning capability (MPC)	0.37/0.54	0.01/0.00	Yes/Yes	0.06/0.22	Small/ Medium-Large
2a/b	Technology quality (TQ) → Marketing planning capability (MPC)	0.24/0.31	0.21/0.04	No/Yes	0.03/0.07	Small/Small-Medium
3a/b	Information quality (IQ) → Marketing implementation capability (MIC)	0.33/0.63	0.02/0.00	Yes/Yes	0.05/0.31	Small/Large
4a/b	Technology quality (TQ) → Marketing implementation capability (MIC)	0.11/0.22	0.48/0.15	No/No	0.01/0.04	-/Small
5a/b	Information quality (IQ) → CRM	0.47/0.35	0.00/0.01	Yes/Yes	0.12/0.08	Medium-Small/Small-Medium
6a/b	Technology quality (TQ) → CRM	0.07/0.47	0.74/0.00	No/Yes	0.00/0.14	-/Medium

Note(s): Low vs high perceived market performance
Source(s): Created by the authors



Source(s): Created by the authors

Figure 2. Graphical illustration of the effect sizes between the low and high perceived market performance responses

Discussion

The main goal of this research was to examine the impact of the quality of BDMA as a resource for enhancing marketing planning, implementation and CRM capabilities so that the influence of low and high perceived market performance of firms on the relationships in the structural model was also analyzed. The research considered the critical attributes of BD quality, i.e. information and technology quality, to test their impact on marketing planning, implementation and CRM capabilities. Our study put together several exciting findings that add to the body of knowledge in this burgeoning area of marketing and BD. *First*, the model illustrated in this research explains more than 65% of the variance in the exogenous constructs of marketing planning, marketing implementation and CRM, thus indicating that technology quality and information quality are robust predictors of the marketing capabilities in question. *Second*, the impact of information quality on marketing capabilities was significant when the respondents perceived the market performance as high or low, indicating the importance of information quality in developing marketing capabilities. *Third*, the impact of technology quality on the marketing capabilities was significant only in cases when the respondents perceived the market performance to be high but not at all when the market performance was perceived to be low. *Fourth*, the effect of information quality on marketing capabilities tended to be markedly higher when the market performance was perceived to be higher than the impact of technology quality on marketing capabilities, except for the influence of information quality on CRM.

This was especially evident in the relationships of "Information quality → Marketing implementation capability," "Information quality → Marketing planning capability," and "Technology quality → CRM" (Figure 2). However, this was not the case for the relationship between information quality and CRM capability; however, the effect sizes were about the same (0.12/0.08) for the low and high perceived market performance responses.

Academic implications

The findings suggest valued insights into the relationship between the quality of BDMA and the marketing capabilities when comparing firms where the market performance was perceived to be either low or high. This is consistent with previous research, as information quality has been significantly related to the quality of managerial decisions (Hakimpoor and Khairabadi, 2018). Furthermore, digital technology, tangible and intangible assets (like information technology and information), and marketing capabilities have been discovered to have a significant role as facilitators of a firm's growth (Foroudi *et al.*, 2017). Also, consistent with the RBV, information quality has been discovered to be a strategic success factor in the performance of CRM (Harrison, 2016).

While prior research has indicated that there is a significant and positive relationship between the *use* of BDMA and a firm's marketing capabilities (Cao *et al.*, 2021), a distinction was made in this study between the "use" and the "quality" of BDMA, as it is evident that there is a difference between the use and the quality of BDMA as the use of marketing analytics does not necessarily guarantee quality. However, the two constructs are highly connected; previous research has found that information quality positively relates to information used in organizations (Khalil and Elkordy, 2005; Popovic and Habjan, 2012). This shows that information quality is of the utmost importance for organizations; information should only be used and applied in decision-making when one knows the information is high-quality.

The results of this research provided significantly higher explanatory power (i.e. the capability of a hypothesis to explain the issues under investigation to which they relate) levels compared to the study by Cao *et al.* (2021) as the R^2 values in this study are almost at the substantial level (0.66–0.72) while the R^2 values in the Cao study can be considered to be weak (0.20–0.24) in social sciences (Hair *et al.*, 2022) again indicating the importance of the quality of information concerning the mere use of information. Accordingly, the low R^2 values cast some doubt on the credibility of the generalizability of the explanations in the Cao *et al.* (2021) study. These differences in the explanatory power (or, more precisely, in-sample predictive power) are further supported by the large "out-of-sample predictive power" values as measured with the Q^2 values (Table 4). These noteworthy differences in the explanatory power can only partially be explained by the fact that there were two exogenous constructs (technology and information quality) present in the structural model of this research instead of only one (use of marketing analytics) in the Cao *et al.* (2021) study. For that reason, previous research has introduced the R^2 adjusted metric, which accounts for this by changing the R^2 value based on the number of explanatory variables concerning the data size and, therefore, is a more conservative estimate than R^2 (Theil, 1961). This study had no differences between the R^2 and R^2 adjusted values (Table 4).

In addition, this research examined the respondents' perceptions regarding the relationships between low and high perceived market performance responses with the assumption that there might be observed *heterogeneity* in the data set, which was the case. Extant literature has pointed out that researchers regularly use recognizable data characteristics to categorize the data and, therefore, decide to assess separate models. Knowing the sources of heterogeneity can be challenging in advance (Hair *et al.*, 2022). However, the fact is that the failure to recognize the source of heterogeneity might seriously distort the conclusions drawn from the data analysis of the aggregate data.

Practical implications

The analysis of the results provides pragmatic evidence about the impact of technology quality and information quality on marketing capabilities. The research empirically demonstrates the value and need to focus on the technology and information *quality* driving BDMA to enhance marketing capabilities. The study also contributes to the marketing practice and extant marketing research by expanding how previous research has examined the effects of BDMA by analyzing the impact of drivers *individually* and in firms where the market performance was either low or high. Looking at the influence of the drivers individually is a crucial investigation because it means organizations are better suited to understand what explicitly drives BDMA to enhance marketing capabilities. Adopting this improved approach is significant in a practical sense because firms will know precisely what causes the outcomes of better decision-making and performance. This also means that resources will be better allocated because firms can focus specifically on the areas generating beneficial results.

The perceived impact of technology and information quality on BDMA differs in terms of the effect size, as the results indicate that information quality has a more critical role than technology quality (Table 5). This can be explained by the fact that good quality information is necessary for successful decision-making, marketing tasks, marketing capabilities and so on; they cannot exist without good information. Technology is an enabling tool that can aid in implementing decisions and planning, but it is not enough to generate positive performance-related outcomes. Technology requires good information to be as helpful as it can be. Nevertheless, firms should use appropriate resources for the quality of information without forgetting the importance of technology quality, as evidenced by the findings among the respondents with high perceived market performance.

Furthermore, information quality has also been found to be a vital component of the value co-creation process both in the B2C (Oh and Teo, 2010; Paredes *et al.*, 2014) and B2B context (Rai *et al.*, 2017). This demonstrates the widespread influence of high-quality information in organizations. Information quality is essential not only in internal marketing capabilities and decisions but also in firms' external relationships. Maintaining high-quality information must be a priority for managers of organizations due to the extensive impact that information quality can have on a wide range of internal and external stakeholders.

Limitations and future research

The research conducted was limited to the US and Canadian marketing personnel with at least limited experience in the deployment of BDMA. Even though most of the BD applications have been undertaken in North America (Statista, 2021), future research should be conducted in other parts of the world to see if the findings are consistent with this research.

Information quality and technology quality as constructs could be further investigated. For instance, examining information and technology quality from the service-dominant logic perspective could be an intriguing avenue of research (Vargo and Lusch, 2004). Information and technology quality could be considered crucial firm resources that actors can exchange to co-create value. Also, it is noteworthy that the perceived market performance was measured with items that perhaps emphasized new products and their success. Future research should enhance the approach taken in this research by adding other market performance-related indicator variables like penetration for existing products, customer satisfaction, net promoter score, and customer profitability.

This research concentrated on the static marketing capabilities of marketing planning and implementation and the dynamic marketing capability of CRM. Future research could also incorporate other static marketing capabilities (e.g. pricing, advertising, promotion and channel management), dynamic marketing capabilities (e.g. market sensing and brand management) and adaptive marketing capabilities (e.g. vigilant market, adaptive market experimentation and open marketing capabilities) to examine if the findings are consistent with this research.

Conclusions

This research aimed to examine the impact of technology and information quality on marketing capabilities in the context of BDMA so that comparisons between low and high perceived market performance were accounted for. Only respondents with at least limited experience in BDMA participated in the survey. Significant differences were absent regarding the information quality construct between the low and high perceived market performance. However, there were some significant differences between low and high perceived market performance for the technology quality construct.

Information quality demonstrated a higher impact than technology quality amongst the survey respondents. Therefore, firms need to invest more in information quality without forgetting the role of technology quality, as evidenced by the respondents who perceived the market performance as high.

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Appendix

	Construct	1	2	3	4	5	6	7	8	9	10	11	12
1	System reliability (SYSREL)	1											
2	System adaptability (SYSADP)	0.79	1										
3	System integration (SYSINT)	0.82	0.77	1									
4	System privacy (SYSPRI)	0.77	0.76	0.75	1								
5	Completeness (COMP)	0.78	0.76	0.79	0.75	1							
6	Currency (CUR)	0.74	0.72	0.76	0.74	0.75	1						
7	Format (FORM)	0.70	0.74	0.73	0.73	0.70	0.73	1					
8	Accuracy (ACC)	0.74	0.74	0.71	0.76	0.72	0.72	0.78	1				
9	Marketing planning capability (MKTPLANCAP)	0.74	0.74	0.73	0.76	0.72	0.74	0.73	0.79	1			
10	Marketing implementation capability (MKTIMPCAP)	0.72	0.73	0.71	0.67	0.69	0.72	0.73	0.74	0.79	1		
11	Customer relationship management (CRM)	0.75	0.75	0.75	0.71	0.74	0.73	0.74	0.73	0.77	0.79	1	
12	Market performance (MKTPERFOR)	0.73	0.69	0.75	0.71	0.72	0.66	0.70	0.70	0.77	0.73	0.76	1

Source(s): Created by the authors

Table A1.
Correlation table of latent constructs

Table A2.
Correlation table of the indicator variables (first-order constructs)*

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	MKTPLANCAP1	1																
2	MKTPLANCAP2	0.55	1															
3	MKTPLANCAP3	0.47	0.53	1														
4	MKTPLANCAP4	0.45	0.53	0.63	1													
5	MKTIMPCAP1	0.50	0.57	0.50	0.43	1												
6	MKTIMPCAP2	0.44	0.61	0.45	0.49	0.47	1											
7	MKTIMPCAP3	0.46	0.53	0.51	0.52	0.51	0.48	1										
8	MKTIMPCAP4	0.42	0.52	0.46	0.50	0.48	0.49	0.46	1									
9	CRM1	0.47	0.48	0.53	0.45	0.46	0.49	0.48	0.56	1								
10	CRM2	0.52	0.56	0.54	0.48	0.57	0.59	0.51	0.50	0.61	1							
11	CRM3	0.41	0.54	0.53	0.55	0.45	0.57	0.47	0.49	0.46	0.58	1						
12	CRM4	0.43	0.43	0.53	0.50	0.43	0.44	0.46	0.49	0.49	0.57	0.51	1					
13	CRM5	0.44	0.48	0.46	0.47	0.52	0.37	0.45	0.51	0.47	0.54	0.55	0.54	1				
14	MKTPERFOR1	0.44	0.50	0.47	0.44	0.47	0.38	0.39	0.42	0.34	0.42	0.47	0.48	0.49	1			
15	MKTPERFOR2	0.53	0.58	0.56	0.54	0.49	0.44	0.53	0.48	0.43	0.51	0.51	0.41	0.54	0.57	1		
16	MKTPERFOR3	0.46	0.52	0.52	0.56	0.43	0.51	0.42	0.60	0.51	0.56	0.52	0.54	0.42	0.53	0.51	1	
17	MKTPERFOR4	0.42	0.47	0.50	0.48	0.42	0.44	0.44	0.46	0.46	0.53	0.56	0.47	0.47	0.50	0.54	0.53	1

Note(s): For the shortcuts, see Table A1
Source(s): Created by the authors

Table A3. Correlation table of the indicator variables (second-order constructs)*

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	SYSREL1	1																							
2	SYSREL2	0.47	1																						
3	SYSREL3	0.52	0.45	1																					
4	SYSADP1	0.46	0.51	0.45	1																				
5	SYSADP2	0.49	0.52	0.48	0.43	1																			
6	SYSADP3	0.65	0.52	0.56	0.43	0.56	1																		
7	SYSINT1	0.63	0.48	0.54	0.49	0.51	0.57	1																	
8	SYSINT2	0.57	0.51	0.56	0.46	0.50	0.64	0.54	1																
9	SYSINT3	0.57	0.54	0.55	0.45	0.49	0.53	0.55	0.51	1															
10	SYSPRI1	0.57	0.55	0.49	0.49	0.41	0.54	0.48	0.53	0.51	1														
11	SYSPRI2	0.50	0.53	0.45	0.49	0.53	0.58	0.48	0.52	0.48	0.49	1													
12	SYSPRI3	0.50	0.46	0.50	0.41	0.46	0.56	0.51	0.55	0.51	0.45	0.53	1												
13	COMP1	0.53	0.45	0.57	0.38	0.52	0.53	0.55	0.50	0.53	0.45	0.47	0.41	1											
14	COMP2	0.53	0.58	0.48	0.46	0.54	0.55	0.57	0.62	0.45	0.56	0.50	0.46	0.47	1										
15	COMP3	0.46	0.53	0.45	0.49	0.48	0.50	0.53	0.47	0.53	0.47	0.59	0.50	0.43	0.52	1									
16	CUR1	0.52	0.41	0.45	0.42	0.41	0.47	0.47	0.46	0.44	0.44	0.39	0.39	0.42	0.48	0.50	1								
17	CUR2	0.55	0.57	0.43	0.46	0.44	0.56	0.52	0.64	0.56	0.51	0.56	0.53	0.52	0.50	0.55	0.44	1							
18	CUR3	0.57	0.44	0.48	0.48	0.49	0.61	0.53	0.53	0.49	0.49	0.60	0.56	0.44	0.59	0.50	0.56	0.58	1						
19	FORM1	0.51	0.46	0.41	0.56	0.45	0.51	0.46	0.44	0.49	0.56	0.54	0.44	0.49	0.44	0.48	0.44	0.54	0.54	1					
20	FORM2	0.55	0.40	0.52	0.42	0.46	0.54	0.54	0.50	0.59	0.52	0.44	0.49	0.49	0.56	0.38	0.46	0.51	0.56	0.52	1				
21	FORM3	0.45	0.49	0.41	0.43	0.55	0.55	0.48	0.50	0.52	0.53	0.48	0.45	0.44	0.48	0.43	0.39	0.50	0.55	0.50	0.56	1			
22	ACC1	0.54	0.32	0.50	0.39	0.40	0.53	0.47	0.40	0.46	0.51	0.41	0.48	0.50	0.41	0.40	0.45	0.43	0.45	0.55	0.57	0.45	1		
23	ACC2	0.45	0.52	0.39	0.50	0.50	0.49	0.44	0.42	0.44	0.44	0.47	0.50	0.46	0.46	0.44	0.36	0.52	0.45	0.50	0.45	0.52	0.44	1	
24	ACC3	0.58	0.51	0.50	0.43	0.49	0.57	0.53	0.52	0.54	0.48	0.62	0.55	0.47	0.54	0.49	0.46	0.54	0.65	0.47	0.56	0.59	0.47	0.47	1

Note(s): For the shortcuts, see Table A1
Source(s): Created by the authors

First order construct	Second order construct	Indicator variable	Mean	Std. dev	Source
Technology quality (CA = 0.92, CR = 0.93, AVE = 0.53)	System reliability Average = 3.82, Std.dev. = 0.83 (CA = 0.74, CR = 0.85, AVE = 0.65)	• System operates reliably for marketing analytics	3.89	1.03	• Akter *et al.* (2017)
		• System performs reliably for marketing analytics	3.81	1.03	
		• Operation of the system is dependable for marketing analytics	3.78	1.01	
	System adaptability Average = 3.78, Std.dev. = 0.86 (CA = 0.73, CR = 0.85, AVE = 0.65)	• System can be adapted to meet a variety of marketing analytics needs	3.90	1.02	
		• System can flexibly adjust to new demands or conditions during marketing analytics	3.71	1.12	
		• System is flexible in addressing needs as they arise during marketing analytics	3.74	1.05	
	System integration Average = 3.79, Std.dev. = 0.94 (CA = 0.78, CR = 0.87, AVE = 0.69)	• System effectively integrates data from different areas of the company	3.91	1.08	
		• System pulls together data that used to come from different places in the company	3.72	1.14	
		• System effectively combines different types of data from all areas of the company	3.73	1.17	
	System privacy Average = 3.83, Std.dev. = 0.90 (CA = 0.74, CR = 0.85, AVE = 0.66)	• System protects information about personal issues	3.91	1.06	
		• System protects information about personal identity	3.78	1.13	
		• System offers a meaningful guarantee that it will not share private information	3.81	1.14	
Information quality (CA = 0.93, CR = 0.94, AVE = 0.55)	Completeness Average = 3.76, Std.dev. = 0.92 (CA = 0.73, CR = 0.85, AVE = 0.65)	• Provides a complete set of information	3.79	1.13	
		• Produces comprehensive information	3.71	1.14	
		• Provides all the information needed	3.77	1.14	
	Currency Average = 3.82, Std.dev. = 0.90 (CA = 0.77, CR = 0.87, AVE = 0.69)	• Provides the most recent information	3.90	1.01	
		• Produces the most current information	3.72	1.16	
		• Always provides up-to-date information	3.77	1.10	
	Format Average = 3.85, Std.dev. = 0.88 (CA = 0.77, CR = 0.87, AVE = 0.68)	• Information provided by the marketing analytics is well formatted	3.93	1.04	
		• Information provided by the marketing analytics is well laid out	3.80	1.07	
		• Information provided by the marketing analytics is clearly presented on the screen	3.83	1.07	
	Accuracy Average = 3.80, Std.dev. = 0.88 (CA = 0.72, CR = 0.84, AVE = 0.64)	• Produces correct information	3.87	1.05	
		• Provides few errors in the information	3.69	1.15	
		• Provides accurate information	3.83	1.09	

Note(s): CA: Cronbach's Alpha, CR: Composite Reliablity, AVE: Average Variance Extracted
Source(s): Created by the authors

Table A4.
Measurement of the second-order constructs (*)

Construct	Indicator variable	Mean	Std. dev	Source
Marketing planning capability Average = 3.83 Std.dev. = 0.82 (CA = 0.82, CR = 0.88, AVE = 0.65)	• Marketing planning skills	3.97	0.95	• Cao *et al.* (2021)
	• Ability to effectively segment and target market.	3.77	1.06	
	• Marketing management skills and processes	3.76	1.02	
	• Thoroughness of marketing planning processes	3.82	1.04	
Marketing Implementation capability Average = 3.77 Std.dev. = 0.84 (CA = 0.79, CR = 0.86, AVE = 0.61)	• Allocating marketing resources effectively	3.82	1.12	
	• Organizing to deliver marketing programs effectively	3.71	1.08	
	• Translating marketing strategies into action	3.74	1.10	
	• Executing marketing strategies quickly	3.83	1.02	
Customer relationship management Average = 3.79 Std.dev. = 0.87 (CA = 0.85, CR = 0.89, AVE = 0.63)	• Routinely establish a "dialogue" with target customers	3.87	1.09	
	• Get target customers to try our products/services consistently	3.79	1.10	
	• Focus on meeting customers' long-term needs to ensure repeat business	3.73	1.12	
	• Systematically maintain loyalty among attractive customers	3.78	1.04	
	• Routinely enhance the quality of relationships with attractive customers	3.78	1.12	
Perceived market performance Average = 3.73 Std.dev. = 0.87 (CA = 0.82, CR = 0.88, AVE = 0.65)	Using marketing analytics has contributed to______ during the last three years relative to competitors • Quicker entry to new markets	3.79	1.07	• Ji-fan Ren *et al.* (2017) • Wang *et al.* (2012)
	• Faster introduction of new products or services to the market.	3.76	1.08	
	• Success rate of new products or services has been higher than our competitors	3.72	1.10	
	• Higher market share	3.64	1.09	

Note(s): CA: Cronbach's Alpha, CR: Composite Reliability, AVE: Average Variance Extracted
Source(s): Created by the authors

Table A5. Measurement of the first-order constructs (*)

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