



The relationship between the quality of big data marketing analytics and marketing agility of firms: the impact of the decision-making role

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Abstract

Against the backdrop of the resource-based and dynamic capabilities view, this paper examines the impact of technology and information quality on marketing agility and the effect of the decision-making role on technology and information quality in the context of big data marketing analytics. Data were acquired from 236 marketing professionals in the U.S. and Canada working in companies with at least limited experience in big data deployment and analyzed with PLS-SEM. The findings indicate that both the information and technology quality are related to the marketing agility of the firms. Moreover, the result also shows a positive and significant association between decision-making role and information quality. This research provides an understanding of the impact of the quality of BDMA on marketing agility as it relates to the quality of information and a firm's technology, as well as the positive relationship of the decision-making on the aforementioned relationships.

Keywords Big data · Big data marketing analytics (BDMA) · Information quality · Technology quality · Marketing agility · Decision-making role · Partial least squares structural equation modeling (PLS-SEM)

Introduction

Using advanced data-driven analytical tools has become an imperative part of marketing management (Basu et al. 2023). In the rapidly changing marketing world, big data marketing analytics (BDMA) has become one of the major driving forces as a tool for customer segmentation, targeting, and retention (Kamel 2023). BDMA helps target the right customers and tailor their marketing strategies for each target group (Indarjo 2021). In applying BDMA, firms must have high-quality technology and information. In information systems (IS) research, technology quality and information quality have been given much emphasis from the perspective of customer value creation (Akter et al. 2017), decision-making (Verma and Mittal 2023), service and customer

satisfaction (Rouibah et al. 2020). From the organizational resources-based view (RBV), technology and information play a vital role in the flexible and prompt adjustment of organizational needs (Zhang et al. 2023). However, how the quality of BDA affects firms' agility is yet to develop in prior research (Morales-Serazzi et al. 2023; ZareRavasan 2023).

The large quantity and variety of data generated by online interactions collected, analyzed, and transformed into actionable insights helps in improving marketing agility (Wang et al. 2021). Through marketing agility, companies can quickly adjust in anticipation and identify customers' demands. Big data analytics (BDMA) allows companies to harness as much data as possible, which can then be processed to derive common patterns in customer behaviour, for example. This will enable companies to remain agile and make meaningful marketing decisions in real time, which helps companies focus not only on potential customers but also on the various industry trends, their competitors, and global market trends (Bhanot 2020). Nowadays, customers are always connected to the internet through computers, smartphones, and tablets. These touch-points enable firms to gain insights into customers' likes, dislikes, interests, and other online activity information (Kaila 2020). Even though there are thousands of information collection sources, researchers and practitioners

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always emphasize the quality of the information (Kamel 2023). A study by Fosso Wamba et al. (2015) mentioned that information quality largely depends on accuracy, completeness, currency, and format. Prior studies have mentioned that information or data from multiple sources helps advanced analytics enhance marketing agility (Zare-Ravasan 2023). Agility is the organization's ability to be flexible and promptly adaptive to the changing demands of its customers (Teece et al. 2016). The collected data allows marketers to target customers more precisely, and as the trends in this data change with time, companies must remain agile in implementing the necessary changes (Campbell 2015). However, inconclusive results were also observed from the study of Fosso Wamba et al. (2015). They mentioned that BDA's quality may negatively contribute to a firm's marketing agility. As such, marketing agility comes into play when an organization rapidly iterates the collected data by making sense of it and executing marketing decisions to adapt to the changing market (Kalaiganam et al. 2021). As a result, firms process data to adapt appropriately and promptly to survive and thrive among their competitors.

With rapid technological advancements in today's fast-paced economy, from the production stage to the invention and adoption of new advanced methodologies (e.g., data mining, machine learning, and predictive analysis), every process is conducted quickly to gain a competitive advantage in the marketplace. Technology quality helps managers by providing accurate knowledge about the changes in the market (Al-Okaily et al. 2023). Previous research has indicated that technology quality in BDA applications is based on system integration, adaptability, reliability, and privacy (Akter et al. 2017). Several researchers have investigated technology quality from the perspective of the decision-making process (Kurilovas 2020) and safety management (Nie et al. 2020). However, the research regarding how technology quality affects agility remains scarce.

In a data-driven marketing firm, the manager is crucial in selecting quality information and technology. In a knowledge-intensive industry, a manager is deemed as the human capital of the firm (Sokolov and Zavyalova 2021). Without being competent in decision-making, a firm couldn't exploit the necessary technology and information they have. For instance, Tesla has proven the impact of marketing agility with novel inventions centred on the ingenuity of their sustainable electric automobiles. Global Data shows Tesla has demonstrated agility through its industry-leading margins (Global Data 2020). The most preferred methodology to reach such results was BDMA. BDMA was utilized to market their products and services and improve customer focus and client services. BDMA refers to analyzing enormous amounts of data collected

from various sources, such as social media, sales transaction records, and images (Hyun et al. 2020).

Human resources are a very valuable asset at an organization's disposal because their capacity to utilize other resources effectively and efficiently, such as information, equipment, and technology, is essential to its success (Cherep et al. 2022). Even though the importance of human capability is emphasized from the RBV perspective (Collins 2021), how managers' decision-making role affects BDA qualities (e.g., information and technology) has not been emphasized much in prior research. Based on the human capital perspective, managers play a role in selecting and allocating resources for the future (Khalique et al. 2023).

Concerning this research and referring to the gaps mentioned earlier, the study would like to posit the following research questions:

RQ₁: What is the association between BDA quality dimensions and marketing agility?

RQ₂: How does the decision-making role affect BDA quality dimensions?

By answering the questions, the study aims to explore the impact of the quality of BDMA on the marketing agility of firms. In addition, we will examine the effect of the respondents' decision-making roles on the perceptions of information and technology quality. This issue has not received much attention in past research. The study will provide academic and managerial contributions to the existing literature. Theoretically, the study will contribute to the resource-based view (RBV) and dynamic capability view (DCV) by incorporating information and technology quality as the firm's resources, which helps achieve adaptability in many circumstances through agility. Here, the study argues that DCV is the extension of RBV (Dubey et al. 2019a, b), and at the same time, DCVs can act as mediators between RBC and firm performance (Lin and Wu 2014; Wu 2017). The study poses that the manager as a human capital helps develop resources for the firm to optimize marketing agility. Managerially, competitive and emerging firms will get some insights into harnessing BDMA in their marketing operation. From a methodological standpoint, the study contributes by applying CB-SEM and PLS-SEM to operationalize the proposed models. Moreover, the study utilized first-order formative and second-order reflective models while defining BDA qualities and their relationship with agility.

The remainder of this paper is structured as follows. The literature review of the research gives insight into BD, BDMA, technology quality, information quality, marketing agility and decision-making role in the context of BDMA and ends with hypothesis development. The methodology,



results and discussion, implications, limitations, future research avenues, and conclusions follow this.

Literature review and hypotheses development

Theoretical underpinning

Studies suggest that the use of BD significantly and positively affects marketing analytics (Cao et al. 2022). Consistently with the resource-based view (RBV), this study treats BD as a vital resource for firms (Ji-fan Ren et al. 2017; Raguseo 2018). Data is collected from different sources over a period of time to aid BDMA. After data collection, the next step is to analyze the data, where organizations understand and harness BD's value. However, some researchers have found that organizations struggle to integrate data into decision-making, which results in data quality problems (Mudau et al. 2024). An analysis of the quality of the BDMA will be provided here to validate its impact on marketing agility, which is treated as a dynamic capability for the firm (Khan 2020). BD and BDA, as a business intelligence field, have become crucial in businesses. According to Statista, 46% of the companies used BDA as a research method (Statista 2022). Finally, the personnel of the firm, with varying degrees of decision-making roles, are perceived as a vital resource of the firm as well consistently with the resource-based view (Gerhart and Feng 2021).

Big data marketing analytics (BDMA)

BD is defined as having a high volume, high velocity, wide variety, and high veracity of structured, semi-structured and unstructured data (Kar and Dwivedi 2020). BDA is a holistic process involving collecting, analyzing, using, and interpreting data for various functional divisions to gain actionable insights, create business value, and establish competitive advantage (Fosso Wamba et al. 2015). In today's business world, BDMA is used to understand customer needs and enhance marketing decision-making for developing high-quality products and services (Saidali et al. 2019). The underlying mechanism of BDMA is to make the data actionable for achieving marketing goals (Haverila et al. 2023).

Many firms may neglect the quality aspect of the data, which may impact the proficient use of BD applications (Sivarajah et al. 2017). A study by the Meta Group revealed that 41% of data warehouse projects fail, mainly due to insufficient data quality, which may contribute to erroneous decisions. This, as such, warrants more research in this area. Data input quality strongly influences the quality of the results based on the "garbage in, garbage out" principle

(Wynn and Sadiq 2019). At the same time, quality data must be consistent with the purpose for which it has been created (Haverila et al. 2023).

Previous research has focused on different research arrays of BD quality. Chi et al. (2020) found BDA to be positively related to the business value of information technology (Chi et al. 2020). Likewise, the relationships between BDA usage, data analytics capabilities, and decision-making quality were examined by Li et al. (2022) in the context of the supply chain. All three relationships were discovered to be significant in the research model. Adrian et al. (2017) found support for this by claiming that poor data quality leads to low data utilization efficiency and brings serious decision-making mistakes.

Further, prior research has also discovered BDA quality's positive and significant impact on BDA user satisfaction and business value (Akter et al. 2017; Ji-fan Ren et al. 2017). Regarding agility, extant research has discovered the positive and significant impact of BDA capabilities on supply chain agility (Dubey et al. 2019a, b). However, research regarding the effect of BDA quality on agility in the marketing context is scarce, and this research aims to contribute to this research gap. The volume and time at which the data is generated make it challenging to clean and analyze the data because BD quality standards or procedures are still in their infancy, and there is currently no standard for BD quality (Cai and Zhu 2015). Furthermore, extant research has argued that the two primary dimensions of BD quality, information and technology quality, determine the degree of the value obtained from BDA (Ji-fan Ren et al. 2017), which needs to get more attention in future research endeavours.

Technology quality

In applying BDMA, technology quality is essential (Haverila et al. 2023). Technology quality, commonly described as system quality, is typically technical and firm-specific, and it develops over time, which makes it difficult to imitate (Fosso Wamba et al. 2019). Technology quality focuses on what is expected of the system in processing, storing, and protecting BD. Four significant technology quality subdimensions are essential in acquiring valuable insights: system reliability, system adaptability, system integration and system privacy (Fosso Wamba et al. 2019). *System reliability* indicates that the platform for analytics is infallible and free from interference. A system that needs to deliver results in real time must always be available and reliable in accuracy and completeness. *System adaptability* refers to how well a platform can adapt to changes in requirements. Generally, it is the extent to which a BDMA system can adapt to different needs in changing situations (Kiron et al. 2014). *System integration* refers to how well the system can accommodate various forms of data. This can be defined as the ability to



integrate multiple data on a BDMA system (Fosso Wamba et al. 2019). *System privacy* indicates how secure and safe the BDMA system is, addressing the aspect of security and privacy in a BD system.

BD is robust, complex, and unique, meaning that defining the right tools for data analytics is essential for firms to make the most of the available data (Kalaignanam et al. 2021). According to a recent study, three out of four firms that have emphasized technology quality as their agile processes experienced a 10% increase in customer satisfaction (Columbus 2016). Holistically, the fit between data, quality and goals is vital in achieving agility in BDA (Ghasemaghaei et al. 2017).

Information quality

Information quality refers to measuring data based on criteria such as accuracy, completeness, format, and currency (Fosso Wamba et al. 2019). *Completeness* signifies the extent to which BDA delivers all the essential information; *accuracy* describes the correctness of the data; *format* focuses on how well the information has been represented; and *currency* refers to the user's perception of how up-to-date the information is (Fosso Wamba et al. 2019). Notwithstanding, defining data quality has proven to be a challenging task, yet not as perplexing as defining data quality for the BDA (Merino et al. 2016). One of the BDA's primary goals is to obtain timely business insights from the data in the context of marketing agility, providing responsiveness and, thereby, value for businesses. This goal, however, cannot be correctly obtained without first acquiring quality data. This signifies the importance of BDA measures, which enable the assessment of data quality and the application of corrective actions to data to ensure the datasets are appropriate and relevant for their purpose (Merino et al. 2016).

Marketing agility

Marketing and market agility have proven to further the firm's dynamic capabilities view (DCV), which are closely related to the BDA (Côte-Real et al. 2020). BDA and marketing agility affect or are related to financial performance, such as profit and growth (Karaboga et al. 2023; Lin and Wu 2014; Zhou et al. 2019). The literature on marketing agility is limited despite ample research on many agility aspects of the firms (Özsomer et al. 2023). Research suggests that BDA enables firms to be agile in their decision-making, which is a vital aspect of marketing, as decision-making needs to be done quickly and effectively to be competitive (Shamim et al. 2020).

Marketing agility is an emerging concept, and many firms have already embraced it. It refers to the speed at which an entity rapidly iterates through various marketing

decisions to adapt to the changing market conditions and comprises four key elements: sensemaking, iteration, speed and decision-making (Kalaignanam et al. 2021). Marketing agility has been conceptualized as a strategy that enables organizations to execute their growth activities through streamlined structures and processes (Homburg et al. 2020). It has been viewed as one of the most essential elements in marketing. Prior research suggests that data analytics orientation is positively linked with marketing agility (Tarn and Wang 2023) and may significantly affect firms' financial performance (Karaboga et al. 2023; Zhou et al. 2019). Therefore, companies must consider any issues that can possibly affect marketing agility. Marketing agility draws many parallels with BDMA, which aptly raises the question of whether the quality of BDMA impacts a firm's marketing agility.

From a strategic perspective, marketing agility is the ability to exploit changing patterns of resource deployment in a thoughtful, purposeful, and rapid way instead of remaining hostage to present plans and existing business models (Doz and Kosonen 2010). From an organizational viewpoint, a firm's ability to cope with rapid, relentless, and uncertain changes while thriving in a competitive environment of continually and unpredictably changing opportunities is fundamental (Gölgeci et al. 2019). The quality of information is a crucial point that enables firms to improve their organizational performance and agility (Ashrafi et al. 2019). Felipe et al. (2016) mentioned that information system capability is significantly associated with organizational agility. Li et al. (2022) found a significant positive association between business intelligence and organizational agility. Information quality relies on a firm's business analytics maturity level (Chen and Nath 2018), which ultimately helps business agility.

On the other hand, technology quality is also imperative in BDA because it forms the base for achieving valuable insights for firms. Technology qualities (e.g., systems, usefulness) are crucial in developing organizational agility (Felipe et al. 2020). Lu and Ramamurthy (2011) mentioned the positive association between information technology quality and organizational agility. BDA should lead to information about the customers organizations use to make marketing decisions. The firms should be ready to accept changes and act swiftly based on the information derived from the BDA process and deploy decisions derived from analyzing BD to achieve a competitive advantage. Therefore, technology and information quality may impact firms' marketing agility (Akter et al. 2016). Based on the above, the following hypotheses are set:

H1: Information quality has a significant and positive effect on the marketing agility of a firm.



H2: Technology quality has a significant and positive effect on the marketing agility of a firm.

Decision-making role

Extant research has recognized that information and technology quality are highly valued by top management (Haverila et al. 2023; Kala Kamdjoug et al. 2019). In many cases, these reviews are based on perceptual evaluations of the executives and are thus subjective. The need for research regarding the role of members at different levels of the organization has been recognized (Cortellazzo et al. 2019), as decision-making at different levels of the firm depends on the quality of information (Ghasemaghaei et al. 2018).

In this study, we would like to argue that the members of the firm who were more involved in the deployment of BDMA applications, such as the primary decision-makers, would have more positive perceptions of the quality of information and technology (Kushwaha et al. 2023). However, the role of the decision-maker has not been considered much in prior research on the quality of information and technology. In prior research, it has been

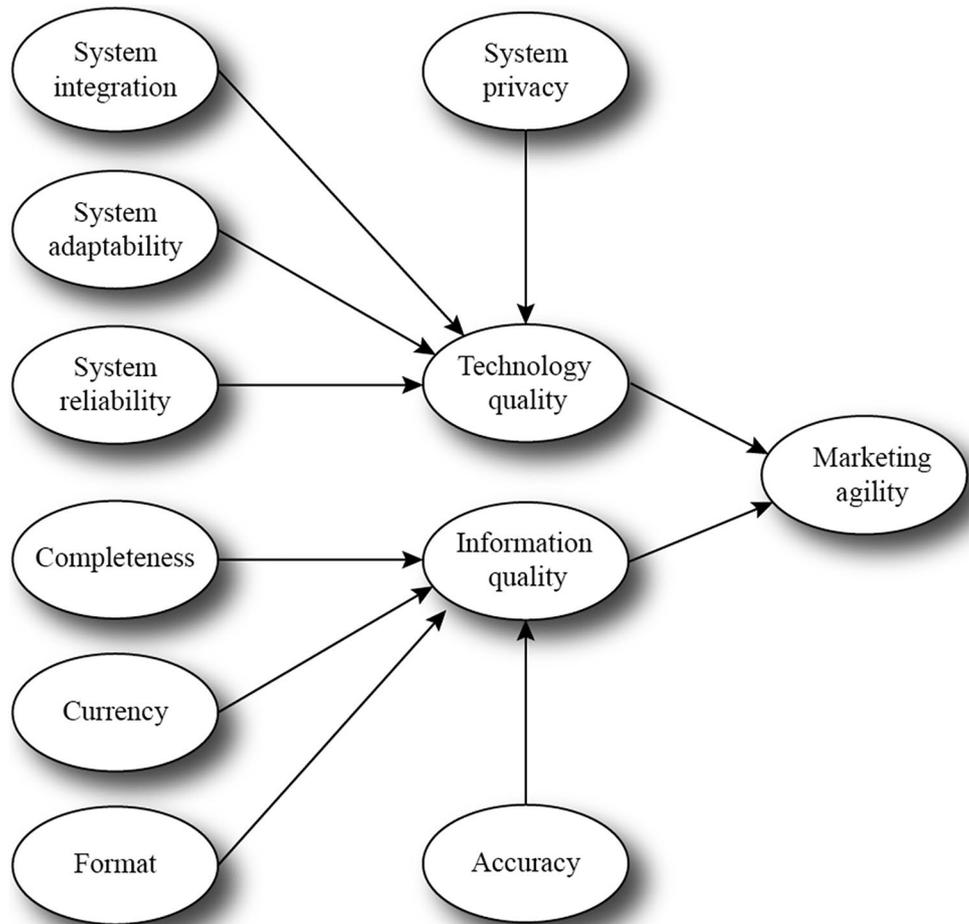
claimed that information should be managed and shared effectively across all levels of the organization concerning enterprise information systems (EIS) and enterprise resource planning (ERP) systems to achieve high performance and effective operation (Samiei and Habibi 2020). This could be considered an obvious expectation. Still, at the same time, it is also feasible that the primary decision-makers perceptions of the key information and technology quality measures may have an impact on the extent to which firms can promptly proceed from making sense of the market and implementing marketing decisions to adapt to the changes in the market, i.e. to be agile in the marketplace (Kalaiganam et al. 2021). Based on the above, the following hypotheses are set:

H3: The decision maker's role significantly and positively affects the information quality.

H4: The decision maker's role significantly and positively affects the technology quality.

Based on the literature review, the following research models were developed (Figs. 1, 2).

Fig. 1 The structural model with lower order constructs and without decision-making role construct



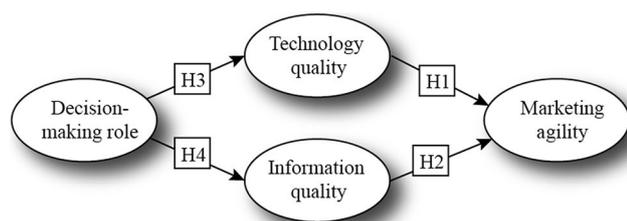


Fig. 2 The structural model without lower order constructs and with the decision-making role construct

Methodology

Sample and respondent characteristics

Survey responses were collected jointly with SurveyMonkey among the marketing professionals with experience in BDMA. In 2021, 970 responses were gathered from Canadian and American respondents with a minimum age of 18. Regarding the sample selection, it is noteworthy that the North American market has a more than 50% share of the global BD and business analytics market. This is followed by Japan (5.7%), China (5.5%), United Kingdom (5.1%) and Germany (4.4%)(Statista 2022). The respondents were financially reimbursed for their time, consistent with SurveyMonkey policies. The survey instrument began with a qualification question as the prerequisite was that the companies where the respondents were working were at least in the limited deployment stage regarding BDMA use (Table 1). The final sample included 236 acceptable responses.

To assess the acceptability of the sample size, Cochran's formula for continuous data was used (Cochran 1977). With an alpha level of 0.025 in each tail of 1.96, an estimated standard deviation in a 5-point scale of 0.8, and an acceptable margin of error of 0.15, a sample size of 137 was needed. To evaluate the sufficiency of the sample size concerning the use of PLS-SEM, extant research has specified that to get a statistical power of 80%, a desired

significance level of 5%, a minimum R^2 of 0.50 and when the number of arrows pointing to a construct is 2, a sample size of 14 is required (Sarstedt et al. 2021). An adequate sample size was reached, given that the final sample contains 236 responses.

Measurement and questionnaire development

The researchers developed a survey questionnaire, where the items were adapted from existing literature and were used to gather the data (Table 2). In assessing the face validity (i.e., researchers' subjective assessments of the presentation and relevance of the measuring instrument), the researchers made a strenuous effort to ensure that the survey instrument was relevant, reasonable, unambiguous and clear (Taherdoost 2016). The questionnaire concentrated on the constructs and their pertinent indicator variables used in the research context. The PLS-SEM method does not restrict the number of indicator variables used (as opposed to the CB-SEM) (Afthanorhan 2013). Consequently, it is possible that using too many indicator variables may introduce redundancy in the measurement of the constructs. This issue, however, is likely to be resolved in the quality testing stage of the measurement model. In this case, redundancy will likely be an issue only for the marketing agility construct, measured with 15 items. As the marketing agility scale was rigorously developed and tested in previous research (Zhou et al. 2019), the researchers decided to use this scale and the other measurement scales in this research.

Method of statistical analysis

The research model was examined using partial least squares structural equation modelling (PLS-SEM). Extant research designates two alternative structural equation modelling methods: covariance-based (CB-SEM) and partial least squares (PLS-SEM). The analysis's measurement viewpoint and objective differ between these methods (Hair et al. 2024). The covariance-based method considers the variance in a variable that is shared with other variables (i.e.,

Table 1 BDMA deployment stage in the respondents' companies

#	The deployment of the 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 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



Table 2 Measurement of the target constructs

	Construct	Indicator variable	Source
Technology quality	System reliability	<ol style="list-style-type: none"> 1. The system operates reliably for marketing analytics 2. The system performs reliably for marketing analytics 3. The operation of the system is dependable for marketing analytics 	Akter et al. (2017)
	System adaptability	<ol style="list-style-type: none"> 1. The system can be adapted to meet a variety of marketing analytics needs 2. The system can flexibly adjust to new demands or conditions during marketing analytics 3. The system is flexible in addressing needs as they arise during the marketing analytics 	
	System integration	<ol style="list-style-type: none"> 1. The system effectively integrates data from different areas of the company 2. The system pulls together data that used to come from different places in the company 3. The system effectively combines different types of data from all areas of the company 	
	System privacy	<ol style="list-style-type: none"> 1. The system protects information about personal issues 2. This system protects information about personal identity 3. The system offers a meaningful guarantee that it will not share private information 	
Information quality	Completeness	<ol style="list-style-type: none"> 1. ____ provides a complete set of information 2. ____ produces comprehensive information 3. ____ provides all the information needed 	Zhou et al. (2019)
	Currency	<ol style="list-style-type: none"> 1. ____ provides the most recent information 2. ____ produces the most current information 3. ____ always provides up-to-date information 	
	Format	<ol style="list-style-type: none"> 1. The information provided by the marketing analytics is ____ well formatted 2. The information provided by the marketing analytics is ____ well laid out 3. The information provided by the marketing analytics is ____ clearly presented on the screen 	
	Accuracy	<ol style="list-style-type: none"> 1. ____ produces correct information 2. ____ provides few errors in the information 3. ____ provides accurate information 	
Marketing agility		<ol style="list-style-type: none"> 1. We can spot the first indicators of new market threats 2. We are often the first to seize new market opportunities 3. We can anticipate new opportunities for market growth 4. We create new preferences by informing customers about new benefits of our products 5. We can respond to changes in demand without overstocking or losing sales 6. We can respond quickly to supply volume fluctuations by having suppliers in many regions of the world 7. When an unexpected threat emerges, we can adjust through resource reconfiguration 8. We can react to fundamental changes with respect to changing the competitor landscape 9. We can market a wide variety of products within our portfolio 10. We can offer different products through minor modifications to existing ones 11. We can adjust what we offer to match market needs 12. We can meet customer's changing needs faster than our competitors 13. We compress time from product concept to marketing to respond quickly to the changes in customer needs 14. We can quickly change our product mix in response to changing market opportunities 15. We are fast at changing activities that do not lead to the desired effects 	
Decision-making role		<ol style="list-style-type: none"> 1. Primary decision maker 2. Major Influence 3. Moderate influence 4. Minor influence 5. No influence 	Haverila et al. (2013)



common variance). At the same time, PLS uses the indicator variables' total variance to generate linear combinations of indicator variables to represent the relevant constructs (Hair et al. 2024). The decision was made to use PLS as the research objective is predicting key target constructs and identifying key driver constructs. The goal is not related to theory testing or confirmation of existing theories. Furthermore, a global goodness-of-fit criterion is not essential, which is necessary for CB-SEM (Hair et al. 2022). Current procedures for using PLS-SEM were followed (Hair et al. 2024) to evaluate the measurement and structural models.

The structural model in this research uses higher-order constructs for technology and information quality, and both are multi-dimensional constructs (Fig. 1). Higher-order constructs allow modelling constructs at a more abstract higher-order dimension and are less concrete than the low-order measurement dimensions. Previous research has indicated that using higher-order constructs decreases the path model relationships under examination and contributes to parsimony. When using this methodology, it is essential to conceptualize and specify the higher-order constructs using thorough measurement theory. The model's evaluation can be done using repeated indicators or a two-stage reflective-formative approach (Sarstedt et al. 2019). The decision was made to use the two-stage indicator method as the model includes 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 equals 1. Therefore, the latent variable score estimates must be added to the dataset instead of trying to estimate the model estimates. Then, in the follow-up analysis, these scores will be used as indicators in the higher-order construct measurement model (Sarstedt et al.

2019). Also, the “decision-making role” construct was added to the model at this stage (Fig. 2).

Data analysis

Background data

Table 3 describes the sample populations in this research. The respondents represented a variety of industries, such as finance and insurance, information and cultural industries, education services, manufacturing, construction, and real estate.

Assessment of the measurement model

The first phase evaluated the individual indicator variables used to measure the constructs. The evaluation of the measurement model starts with the assessment of indicator reliability. A bias-corrected and accelerated bootstrapping analysis was done to determine the significance of indicator variables. The results can be seen in Table 4 and indicate that all loadings were greater than 0.70 except for one marketing agility indicator. Still, as all the relationships were significant to their relevant construct, there was no reason to remove any indicator variables (Rosenbusch et al. 2018). It is to be noted that extant research by Zhou et al. (2019) denoted marketing agility to be a four-dimensional construct of proactiveness, responsiveness, flexibility, and speed. The exploratory factor analysis (EFA) of the marketing agility endogenous construct established, however, that the marketing agility construct was, in fact, one-dimensional (variance explained 52.7%).

Table 3 Background of the sample

#	Country of residence	<i>N</i> = 236 (%)	#	Years with the firm	<i>N</i> = 236 (%)
1	Canada	34 (14.5%)	1	Less than year	15 (6.4%)
2	United States	199 (84.3%)	2	2–5 years	73 (30.9%)
3	Other	3 (1.2%)	3	6–10 years	77 (32.6%)
#	Age group		4	11–15 years	39 (16.5%)
1	19–24	55 (23.3%)	5	16–19 years	11 (4.7%)
2	25–28	34 (14.4%)	6	Over 20 years	21 (8.9%)
3	29–34	55 (23.3%)	#	Education	<i>N</i> = 236 (%)
4	35–40	36 (15.3%)	1	High school or less	28 (11.8 %)
5	41–45	18 (7.6%)	2	Some college—no degree	23 (9.7%)
6	46–54	14 (5.9%)	3	College diploma	25 (10.6 %)
7	55–64	17 (7.2%)	4	Associate	20 (8.5 %)
8	+65	7 (3.0%)	5	Bachelor's	70 (29.7 %)
			6	Master's	45 (19.1 %)
			7	Doctorate	21 (8.9 %)
			8	Other	4 (1.7 %)



Table 4 Measurement model results

Construct	Indicator variable	Outer weights	Outer loadings	(5% bias-corrected confidence interval)		Significance ($p < 0.05$)
				2.5%	97.5%	
System reliability	The system operates reliably for marketing analytics	0.43	0.83	0.78	0.86	Yes
	The system performs reliably for marketing analytics	0.40	0.79	0.70	0.84	Yes
	The operation of the system is dependable for marketing analytics	0.40	0.81	0.74	0.85	Yes
System adaptability	The system can be adapted to meet a variety of marketing analytics needs	0.38	0.75	0.68	0.81	Yes
	The system can flexibly adjust to new demands or conditions during marketing analytics	0.40	0.82	0.75	0.86	Yes
	The system is flexible in addressing needs as they arise during the marketing analytics	0.45	0.85	0.80	0.88	Yes
System integration	The system effectively integrates data from different areas of the company	0.40	0.84	0.78	0.88	Yes
	The system pulls together data that used to come from different places in the company	0.41	0.83	0.77	0.87	Yes
	The system effectively combines different types of data from all areas of the company	0.40	0.82	0.76	0.87	Yes
System privacy	The system protects information about personal issues	0.41	0.80	0.73	0.84	Yes
	This system protects information about personal identity	0.42	0.83	0.77	0.88	Yes
	The system offers a meaningful guarantee that it will not share private information	0.41	0.81	0.75	0.85	Yes
Completeness	The system provides a complete set of information	0.41	0.78	0.71	0.84	Yes
	The system produces comprehensive information	0.43	0.83	0.77	0.87	Yes
	The system provides all the information needed	0.41	0.81	0.73	0.86	Yes
Currency	The system provides the most recent information	0.37	0.79	0.71	0.85	Yes
	The system produces the most current information	0.41	0.82	0.76	0.87	Yes
	The system always provides up-to-date information	0.43	0.87	0.83	0.90	Yes
Format	The information provided by the marketing analytics is well formatted	0.40	0.81	0.75	0.86	Yes
	The information provided by the marketing analytics is well laid out.	0.41	0.84	0.79	0.88	Yes
	The information provided by the marketing analytics is clearly presented on the screen	0.39	0.83	0.77	0.87	Yes
Accuracy	The system produces correct information.	0.40	0.79	0.71	0.84	Yes
	The system provides few errors in the information	0.40	0.79	0.70	0.85	Yes
	The system provides accurate information	0.45	0.83	0.77	0.87	Yes
Marketing agility	We can spot the first indicators of new market threats	0.09	0.71	0.62	0.78	Yes
	We are often the first to seize new market opportunities	0.09	0.72	0.65	0.78	Yes
	We can anticipate new opportunities for market growth	0.10	0.72	0.64	0.77	Yes
	We create new preferences by informing customers about new benefits of our products	0.10	0.75	0.68	0.81	Yes
	We can respond to changes in demand without overstocking or losing sales	0.09	0.73	0.65	0.79	Yes
	We can respond quickly to supply volume fluctuations by having suppliers in many regions of the world	0.08	0.72	0.64	0.79	Yes
	When an unexpected threat emerges, we can adjust through resource reconfiguration	0.09	0.73	0.66	0.79	Yes
	We can react to fundamental changes with respect changing the competitor landscape	0.09	0.72	0.64	0.78	Yes



Table 4 (continued)

Construct	Indicator variable	Outer weights	Outer loadings	(5% bias-corrected confidence interval)		Significance ($p < 0.05$)
				2.5%	97.5%	
	We can market a wide variety of products within our portfolio.	0.09	0.72	0.65	0.78	Yes
	We can offer different products through minor modifications to existing ones	0.09	0.71	0.63	0.77	Yes
	We can adjust what we offer to match market needs.	0.10	0.76	0.68	0.81	Yes
	We can meet customer's changing needs faster than our competitors	0.09	0.75	0.68	0.81	Yes
	We compress time from product concept to marketing to respond quickly to the changes in customer needs	0.10	0.74	0.68	0.79	Yes
	We can quickly change our product mix in response to changing market opportunities	0.09	0.73	0.65	0.78	Yes
	We are fast at changing activities that do not lead to the desired effects	0.09	0.67	0.58	0.75	Yes

Table 5 Construct reliability and convergent reliability

Construct	Cronbach's Alpha	Composite Reliability	average Variance Extracted (AVE)
Accuracy	0.72	0.84	0.64
Completeness	0.73	0.85	0.65
Currency	0.77	0.87	0.69
Format	0.77	0.87	0.68
Information quality	0.92	0.93	0.53
Marketing agility	0.94	0.94	0.53
System adaptability	0.73	0.85	0.65
System integration	0.78	0.87	0.69
System privacy	0.74	0.85	0.66
System reliability	0.74	0.85	0.65
Technology quality	0.93	0.94	0.55

The next step in assessing the measurement model is the assessment of internal consistency reliability (Table 5). Extant literature has pointed out that Cronbach's alpha (threshold > 0.70) is a conservative measure of reliability. In contrast, the composite reliability (target range 0.70 and 0.95) overestimates internal consistency reliability. Thus, the actual reliability is between Cronbach's alpha and composite reliability values (Hair et al. 2022). Consequently, based on the results in Table 5, the internal consistency reliability can be considered acceptable. In terms of convergent validity, usually assessed with the average variance extracted (AVE) values, the accepted threshold level of 0.50 was exceeded (Table 5).

The next step is the assessment of discriminant validity, which specifies 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 case of higher-order models due to the use of repeated indicators. Extant research has indicated that there is only the need to assess the higher-order component as part of the structural model regarding discriminant validity.

This was previously done with Fornell and Larcker's (1981) assessment. Recent literature suggests using the Heterotrait-Monotrait (HTMT) of the correlations, which signifies the ratio between-trait and within-trait correlations (Hair et al. 2022). Previous research has suggested that the threshold value of 0.90 should not be exceeded (Henseler et al. 2014). It is to be noted, however, that 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 for that reason, bootstrapping procedures should be applied to test the significance (Hair et al. 2011, 2019). If the bootstrap confidence interval includes the value of 1, it means a lack of discriminant validity. As seen from Table 6, none of the confidence intervals included the value of 1. Thus, discriminant validity was achieved even though one of the HTMT values slightly exceeded the threshold of 0.90.

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 variance inflation factors (VIF). All VIF values in the measurement model were below the



Table 6 Bootstrapping significance of the Heterotrait–Monotrait correlations

	HTMT	2.5%	97.5%
Marketing agility → Information quality	0.85	0.79	0.89
Decision-making role → Information quality	0.39	0.28	0.49
Decision-making role → Marketing agility	0.35	0.23	0.46
Technology quality → Information quality	0.91	0.88	0.94
Technology quality → Marketing agility	0.87	0.81	0.91
Technology quality → Decision-making role	0.40	0.28	0.50

threshold value of 3; thus, there were no collinearity issues (Hair et al. 2011, 2019).

The next step is the assessment of predictive validity, which is usually done with the R^2 , R^2 adjusted and Stone-Geisser Q^2 values (Geisser 1975; Stone 1974) for the endogenous construct of marketing agility. The results indicate the R^2 value of 0.77, R^2 adjusted value of 0.77 and Q^2 value of 0.54. Extant research has established that R^2 values of 0.75, 0.50 and 0.25 can be described as substantial, moderate, and weak, respectively. Recent research has also established strength criteria for the Stone-Geisser Q^2 values so that values larger than 0.25 and 0.50 represent medium and large predictive relevance in the PLS model (Hair et al. 2020). On this basis, it can be claimed that there is a substantial predictive strength and relevance for the endogenous construct of marketing agility.

Finally, the extant research suggests testing for endogeneity, which happens when a predictor construct is correlated with the error term of the dependent construct (Hair et al. 2022). An essential issue in this regard is the nature of the research, i.e., whether the purpose of the research is primarily prediction or explanation. Previous research has indicated that there is usually a balance between these; therefore, testing for endogeneity is necessary. A suggested method is the Gaussian Copula method, which can now be done directly in the latest version of Smart-PLS (4.0.9.6) (Hult et al. 2018). Before doing this, examining whether the constructs that potentially reveal endogeneity are nonnormally distributed is necessary. This was done by administering the Kolmogorov–Smirnov test with Lilliefors correction on the standardized composite scores readily available in PLS-SEM

(Sarstedt and Mooi 2019). The results indicate that none of the constructs' composite scores showed nonnormal distributions, meaning that none of the constructs can be considered endogenous for the Gaussian Copula analysis. The Gaussian Copula analysis was run in PLS-SEM to confirm this, and the results indicate no endogeneity in the data.

Testing of the hypothesis

The final step in assessing the structural model is the estimation of the path coefficients, which coincides with the hypotheses testing (Table 7).

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). Previous research has expressed that statistical significance is insufficient when recording the research outcomes and that effect size should also be stated (Cohen 1992; Kline 2005). The effect size may be the most significant discovery in statistical analysis as, with an adequately large sample size, statistical testing can find significant differences which are unimportant in practice. For that reason, reporting only the p -values is inadequate (Sullivan and Feinn 2012). It is also noteworthy that the effect size is not affected by sample size; consequently, it is equivalent between various research projects (Hair et al. 2010).

Discussion

The study examines the relationships between BDMA qualities (information and technology) and marketing agility. On the other hand, the impact of the decision-making roles on BDMA information and technology quality was also investigated. Consistently with the previous research, this paper treated the BD quality dimension as having two separate dimensions of technology and information quality: this time in the BDMA context, however. The approach taken here confirms the validity of the approach taken in previous research (Akter et al. 2017).

This research confirms the positive and significant relationship between information and technology quality and marketing agility (Ashrafi et al. 2019). Previous research

Table 7 The significance of the path coefficients in the model in the whole dataset

#	Exogenous construct	Path coefficient	p -value	Hypotheses support	Effect size (f^2)	Effect size description
1	Information quality → Marketing agility	0.33	0.00	Yes	0.08	Medium to small
2	Technology quality → Marketing agility	0.50	0.00	Yes	0.24	Medium to large
3	Role → Information quality	0.39	0.00	Yes	0.18	Medium to large
4	Role → Technology quality	0.40	0.00	Yes	0.19	Medium to large



has discovered that higher information capacity is associated with better marketing agility (Banker et al. 2006), which is congruent with the findings of this research. The results of this research bring a new dimension of information, i.e., the quality related to marketing agility. The results of this research are consistent with extant research so that firms with high information capability that have good quality data are more agile in, for example, new product development and can achieve competitive positions in a shorter period when facing changes in the market environment (Pavlou and Sawy 2011). This illustrates the role of information capability in providing relevant information when firms need to be more agile. The study's result confirms that a firm's resource-based view (RBV) helps in developing dynamic capability (DC). In our research, we argued that BDMA information and technology quality are the firm's resources that assist in building the firm dynamic capability of marketing agility (Haverila et al. 2023). Furthermore, the outcome regarding the relationship between technology quality and marketing agility is consistent with the previous research work (Zain et al. 2005) as it has a significant and direct effect on the marketing agility of firms. This is consistent with the previous research, which has established RBV to be an antecedent of DCV (Lin and Wu 2014; Wu 2017).

Another interesting research finding is the strength of the relationships between information quality and marketing agility and between technology quality and marketing agility. Both relationships are significant, but interestingly, there is a large difference in the effect sizes (Table 7), so the effect size between the technology quality and marketing agility is notably larger than the effect size between information quality and marketing agility. It appears that previous research has not made a distinction in this regard. In a related paper, the impact of information and communication technologies (ICT) on agility was investigated in the supply chain context, and a significant relationship was discovered. However, the ICT construct was treated as a single construct; thus, no distinction between information and technology was made (Garcia-Alcaraz et al. 2017). Another study examined the relationships between IT skills, knowledge, supply chain agility, IT infrastructure, and supply chain agility (Dehgani and Jafari Navimipour 2019). Both relationships were discovered to be significant, but no attention was paid to the effect sizes. In another study, various antecedents of marketing agility were mentioned as applicable routines, processes, flexible structures, and cultural norms (Kalaignanam et al. 2021). The items mentioned were, however, at the organizational level and thus not related to information technology. Furthermore, the study was conceptual, and therefore, the impact of the antecedents on marketing agility was not examined.

Finally, the impact of the decision-making role on the respondents' perceptions concerning information and technology quality was examined. The decision-making role was evaluated with a categorical variable (primary decision maker, major influence, moderate influence, minor influence, and no influence). The hypotheses (3 and 4) were accepted, and effect sizes were classified as medium to large for the information and technology quality. These results are consistent with previous research as top management appreciates information and technology quality (Kala Kamdjoug et al. 2019; Peslak 2014), which is particularly evident in knowledge-intensive endeavours (Eppler 2003) like BDMA. This could be explained by the fact that managers at higher organizational levels may have better knowledge about the actual impact of information and technology quality on the various aspects of business. At the same, it is also discernible that to advance from making sense of the market and implementing marketing decisions to adapt to the changes in the market, the perceptions regarding the information and technology quality must be at a high level at all levels of the organization (Kalaignanam et al. 2021).

Implications

The research has brought forward a few intriguing implications for practitioners and the academic marketing analytics profession. BDMA's practical implications and usefulness are clear for marketing agility and lead to effective and nimble marketing, generating more revenue opportunities and better operational marketing efficiency, creating competitive advantages over rival companies (Jelonek 2017).

The positive contribution of technology quality on marketing agility with a *medium to large* effect size was realized. This shows that the technology used for analyzing data seems vital for an organization to enable agility in the marketing processes, such as recognizing customer needs, constructing an effective customer-driven marketing strategy, creating profitable customer relationships, and capturing value in the marketplace. This demonstrates the importance of having the correct data and information and the right technology and tools to turn the information into relevant marketing insights. Furthermore, for a company to make better marketing decisions faster and timelier, visualization tools (e.g., Tableau, Dunda AI, Jupyter, and GoogleCharts), for example, may help in data conception and comprehension, allowing leaders to address pressing marketing issues (Court 2015). Specifically, regarding technology quality, it is essential to ensure that systems are reliable, adaptable, well-integrated and can provide customers privacy. Reliability can, for example, be achieved by utilizing the redundancy concept by taking several



duplicates of the critical information systems components. Adaptability can be enhanced by enabling multiple ways to interact with the BD systems to provide services when the needs change. Integration is another critical component regarding BDMA, as the data sources are versatile. Then, it is crucial to ensure that interfaces between the various data sources are operational and in sync. The goal of privacy is to ensure that the data is available to the right persons only so that the General Data Protection Regulation (GDPR) is respected, for example.

The information quality was also significantly and positively related to marketing agility, albeit with a *medium to small* effect size. As companies focus on utilizing BD in marketing, especially in applications like social media and social networking, they are constantly challenged with assimilating large volumes of data from an extensive array of sources. The bigger challenge is improving the quality of the information in large quantities. Large volumes of data and information may eventually lead to more ambiguity and uncertainty, which may negatively impact the efficiency of the company's reactions toward the fast-paced and competitive marketing environment. Thus, marketing managers focused on developing marketing agility should be more invested in reducing these negative impacts of uncertainty and ambiguity in marketing processes, which can be achieved through better information quality (Wu and Wang 2017). Accordingly, good data and information quality analysis enable companies to gain greater marketing insights and more actionable marketing intelligence for the key stakeholders. From the perspective of generating revenue and reducing marketing costs and capital, the importance of the information quality of BD is likely to be significant. Thus, customer value can be driven more efficiently using good-quality information with advanced BDMA (Columbus 2016). Specifically, regarding information quality, it is crucial to ensure that the data is accurate, complete, in the correct format and current. This can be achieved by using reliable data sources, recording the data accurately, using standardized data entry processes, examining outliers, and assigning appropriate permissions to change the data.

The McKinsey Consulting Company gathered a group of leaders actively utilizing BDA to achieve business success (Court 2015). Surprisingly, almost three-quarters of the participants could not initially gain meaningful revenue increases or cost improvements. Senior managers were reluctant to invest in large-scale BD projects since these early efforts did not yield immediate and significant results. On this basis, it is feasible to conclude that Chief Analytics Officers and Directors of Marketing Analytics need to examine BD beyond the narrow view of instant positive results; instead, they should adopt a more holistic perspective and consider aspects like information and technology quality (Svilar et al. 2013) to obtain more

meaningful results from BDMA. Thus, the results of this research may help in the deployment of BDMA and the achievement of better marketing agility for firms.

Limitations and future research

This research has some limitations that must be addressed. Firstly, the research was carried out using a cross-sectional design where the researcher simultaneously evaluates the study results (Setia 2016). Further research can be carried out using a longitudinal research design where the same study participants are continuously and repeatedly examined over a more extended period to see what the long-term effects (Wagner et al. 2018) of using BDMA are as well as to examine how individual perceptions regarding BD and BDMA may change over time.

Secondly, as this research did not pose any particular interest in specific industries and sectors, it may be a worthwhile idea to examine if any differences exist between various industries in the context of this research. Third, the major constructs of this research were information quality, technology quality and marketing agility. An organization trying to adopt marketing agility should follow a more holistic approach and concentrate on specific functions of the firm, including marketing and information technology. A 2018 survey conducted by New Vantage Partners shows that nearly 33% of businesses are culturally resistant to change toward agility, and 25% of companies have insufficient organizational alignment and agility (Slesar 2021).

Fourth, previous research has discovered the importance of a data-driven culture in contributing to the firm's performance (Karaboga et al. 2023). Similarly, it would be interesting to add this construct to the research model and examine its impact on marketing agility. It would also be interesting to investigate the impact of the firm's agility-driven culture and its implications for marketing agility. This would likely mean the development of a relevant measurement scale to assess agility-driven culture, as there appears to be a void in the relevant research.

Fifth, as previous research has introduced other possible antecedents of marketing agility, including adaptive marketing capabilities, market-focused strategic flexibility, market orientation, and market-based organization learning (Kalaiganam et al. 2021), bringing them into the framework of this research would be an attractive future research venue to enhance the quality measures (e.g., effect size) of the structural model used in this research.

Finally, the study focused on the quality of BDMA and its impact on the marketing agility of firms. The analysis only focused on two components of BD quality: information quality and technology quality. Future research could include other features like application



and talent quality and evaluate their impact on marketing agility.

Conclusions

The paper aimed to examine the relationship of information and technology quality with marketing agility so that the impact of the decision-making role on the strength of the relationships was also discussed. BDMA can be acknowledged as an essential answer for coping with the vast scale of the challenges associated with the prevailing volatility in the marketing environment. The information and technology quality related to improving marketing agility is part of the issue linked to this phenomenon. As firms try to satisfy the increasingly dynamic needs of their target customers, the question of whether such marketing efforts will be successful lingers, necessitating the demand for high-quality BDMA to tackle the issue. In this research, information quality, technology quality and marketing agility were combined into the same structural model to develop a more holistic view of how the quality of BDMA can help firms build on their marketing agility to respond speedily to marketing opportunities in the competitive marketing environment, which may enhance the firm performance.

The research shows that information quality is positively and significantly related to marketing agility with a medium to small effect size and technology quality with a medium to large effect size. When combining the right technology and excellent quality data, companies can find solutions to marketing problems in real-time and achieve rapid market testing, thus becoming agile in marketing. It was also noteworthy that the managers with higher decision-making abilities had more positive perceptions about the strength of the relationships. Furthermore, to achieve marketing agility in the truest sense, an agile firm must align itself with appropriate marketing goals, analyze marketing data to identify marketing opportunities, perform market testing and go back to the marketing ideas based on real results. Hence, firms must prioritize their investment in BDMA as this provides the foundation for superior marketing agility performance.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical Approval Ethics approval received from Thompson Rivers University (#103375).

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