The Impact of Quality of Big Data Marketing Analytics (BDMA) on the Market and Financial Performance

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ABSTRACT

Impact of quality of big data marketing analytics (BDMA) was analyzed, with special attention to the BDMA dimensions of technology and information quality, and the level of deployment on perceived market and financial performance. The sample was collected with Canadian and U.S. marketing respondents with experience in big data (BD) deployment (N=236). The model analysis was done with PLS-SEM. The study highlights how technology and information quality are related to the market and financial performance with high predictive validity and strength. Also, the level of deployment had a significant impact on both the technology and information quality in BDMA. The study provides an understanding of how the level of deployment impacts BDMA technology and information quality dimensions; and how they individually contribute to the enhancement of a firm's market and financial performance from the perspective of marketing personnel with experience in deployment of BDMA. It is also evident that the more advanced the firm is in the deployment of BD, the higher the technology and information quality.

KEYWORDS

Big data marketing analytics, Financial performance, Information quality, Level of deployment, Market performance, Technology quality

THE IMPACT OF QUALITY OF BIG DATA MARKETING ANALYTICS (BDMA) ON THE MARKET AND FINANCIAL PERFORMANCE

Big data (BD) has surfaced as a frontline in business for determining competitive advantage and utilizing opportunities (Frisk, 2017). Firms are collecting unprecedented amounts of data as they pursue enhanced business strategies to harness BD analytics that aid in marketing and functions like supply chain management (Zhong et al., 2016), operations management (Choi et al., 2018), finance (Fang & Zhang, 2016), human resource management (Zang & Ye, 2015), and the public sector

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(Desouza & Jacob, 2017). The extant literature recognizes BD as the "next management revolution" (McAfee & Brynjolfsson, 2012), as well as the "new raw material for business" (Cukier, 2010) or the "new science that holds the answers" (Gelsinger, 2012).

BD portrays large volumes of structured and unstructured data that shape the business ecosystem and the systematic processing of the immense amount of data for more robust decision-making and strategic initiatives. Organizations use big data marketing analytics (BDMA) to enhance marketing operations, deliver better customer service, generate tailored marketing campaigns, and perform activities that contribute to increased revenues and profitability (Ji-Fan Ren, 2017; Sharma et al., 2014). It can be claimed that BD, from marketing communication channels, such as social media, can deliver information paired with legacy consumer behaviour methods while offering supplementary benefits to marketers.

Despite these advantages, utilizing BD can be difficult. For example, more than a singular database may be required for marketing. Furthermore, commitment to customers, information privacy, and legal constraints must be considered when adopting BD analytics (Even et al., 2010).

BD is collected from different sources via automated means; therefore, the quality and usefulness of the data cannot be ensured. There are limitless chances of improper, erroneous data collected alongside valuable data during the collation of BD. Sustaining a good quality BD database or data warehouse necessitates extensive effort. Organizing a BD for analysis often requires more time than the analysis itself (Hofacker et al., 2016).

While BD is a valuable knowledge asset in marketing, high-quality data is required for companies to obtain competitive value and enhanced confidence in the output quality from big data analysis (BDA). Additionally, the users of BD will be able to produce more and concentrate on essential activities (Corte-Real et al., 2019). Research has indicated that the level of BD management impacts value creation (Chen et al., 2014). Despite the claims that BDA and data quality enhance business value, there is inadequate knowledge of the impact of quality dimensions on financial and marketing performance from the marketing perspective (Gupta & George, 2016; Wamba & Mishra, 2017).

There needs to be more research on the impact of the level of deployment on the technology and information quality aspects of information technology (IT) systems. Some studies have discussed the level of deployment when assessing the impact of the IT (Prattipatti & Pegels, 1996), recognizing the lack of comparable IT measures when evaluating the impact of IT systems. The concept of the level of deployment is not new to research (Kanuku, 2019; Vaidya & Campbell, 2016). However, the use of the level of deployment measure when investigating its impact on technology and information quality in BDMA applications has been limited. Thus, this study will assess the impact of the level of BD deployment on the technology and information quality of BDMA, as well as the impact on the perceived market and financial performance.

LITERATURE REVIEW

Big Data

BD has become an interesting opportunity for marketing over the last ten years. Many companies use BD to analyze and decipher transactional and traffic data, monitor marketing actions, estimate customer needs and employ new marketing programs (Octoparse, 2021).

BD is described through the following dimensions (or the four Vs):

1. **Volume:** Volume, the amount of BD, is the original attribute of BD (Dea, 2015). The current online population is gigantic, with more than 8 billion cell phone subscriptions (Statista, 2021a), 3 billion Facebook users (Statista, 2021b), and more than 370 billion e-mails sent per day (Statista, 2021c). These numbers signify the increased volume of data.

2. **Velocity:** Velocity is the rate at which new data is generated (Dea, 2015). Internet platforms contributed to 64.2 zettabytes (10^{21}) of data in 2020. By 2025, global data will exceed more than 180 zettabytes (Holst, 2021).
3. **Variety:** Variety of BD refers to the many forms of BD, such as structured, unstructured, and semi-structured. Structured data, like financial transactions, are defined with specific rules. This, however, is not the case with unstructured data, including pictures, voices, tweets, etc.
4. **Veracity:** Veracity measures the accuracy of data. BD veracity indicates potential bias, insignificance, and irregularity in the data. This contributes to data trustworthiness. It is challenging to store the data while ensuring it is meaningful for the issue at hand (Ellars, 2013).

The data from social media are collected through likes, shares, follows comments, tweets, and retweets. This data contributes to the acquisition of deep marketing insights into consumer behaviour. To create an immersive view of the customer base, firms need to collect, store, and analyze an overabundance of data (Bekker, 2017). For instance, firms can collect data on the products a customer is putting in the shopping cart, the kind and quantity of purchases, and the feedback provided by the customer. The firm can quickly adjust its promotions and marketing activities based on actual and changing consumer behaviour.

The efficient use of BDMA should increase sales, enhance the quality of sales and data on leads, and enhance territory planning for the sales teams. These are examples of where BD can significantly contribute to the marketing (Malhotra, 2016). In marketing, BD provides insights into which content (e.g., in social media) is the most effective at each sales phase. It also highlights methods to improve investments in customer relationship management (CRM), enhance conversion rates, improve prospect engagement, and increase revenues and customer lifetime value (CLV) (Columbus, 2016).

Customer and operational analytics, fraud and compliance, new product and service novelty, and data warehouse optimization are common uses for BD in marketing. Firms should, therefore, thoroughly analyze BD to augment their market and financial performance. Research claims that the main difference between successful and unsuccessful companies is the ability to analyze BD accurately. Effectively utilizing BD can aid marketing teams in optimizing their marketing campaigns, accelerating workflows and enhancing customer loyalty (Schmidt, 2021).

Extant research indicates that high-quality data may lead to better predictive power and customer insight. The overall quality dimensions in BD may connect with improved business value and performance (Taleb et al., 2018). Its applicability in a marketing context has yet to gain much attention in academic research, despite the marketing function being the primary interface between the company and its customers (Czinkota et al., 2021).

Big Data and Level of Deployment

The level of deployment concept has yet to be the primary research (e.g., Chen et al., 2015). Deployment can be defined as the act of bringing resources into practical action. It includes the steps, processes, and activities required to make a software system available to intended users (Sumo Logic, 2021), which applies to software deployment (e.g., BDMA). It also proceeds in different levels (Science Direct, 2021), ranging from complete unawareness to full deployment (Murphy & Cox, 2016).

Gunasekaran et al. (2018) used the concept when assessing the level of deployment of the agile manufacturing facilitator. The study found that firms with higher levels of deployment of IT systems achieved higher levels of attainment in competitive objectives like quality conformance and technology levels. In another study, Vidiasova et al. (2017) asked experts to benchmark smart cities with criteria like the economy, smart living, smart government, smart people, mobility, and environment regarding the level of deployment. Finally, Orlandi et al. (2020) used a multi-dimensional measure to assess social media analytics technology-related deployment and its impact on technology-sensing capabilities in a complex structural model. The study discovered that it was significantly and positively related to technology-sensing and technology-responding capabilities.

Furthermore, the study evaluated the influence of social media analytic skills and marketing/IT integration on social media analytics technology-related deployment. In conclusion, the level of deployment is a concept introduced previously in relevant research. However, its use has been casual or narrow in focus, especially in the context of BD.

Technology Quality

Technology quality and information quality are vital to enhancing the quality of decision-making, business value, and firm performance in a BD ecosystem (Ji-Fan Ren, 2016). Firms are challenged with changing customer demand, increased competition, and technological progression (Roberts & Grover, 2012). The digital transformation of organizations, the emergence of new channels, and a flood of customer data are significantly altering marketing practices (Swaminathan et al. 2020). Thus, technology quality in BDMA is a crucial factor that affects business. It is a critical ingredient in determining the information system quality, which impacts the output quality. Technology quality reflects the quality of the analytics platforms, a function of reliability, adaptability, integration, and privacy of the systems (Akter et al., 2017). It characterizes the quality of information processing, described by state-of-the-art technology, a system with critical functions and features that supply a user-friendly, easy-to-learn, and supportable software application (Gorla et al., 2010). It is also likely that the level of deployment impacts all dimensions of technology quality because experience and learning throughout the deployment process affect technology quality (Love et al., 2015; Manley & Chen, 2017).

System integration denotes the capability to incorporate data from various sources to produce meaningful insights (Akter et al., 2017). Technology should efficiently integrate heterogeneous datasets as it uncovers underlying relational patterns quickly. System integration that integrates multiple datasets from a diverse set of sources can enhance the speed and ease of data accessibility to relevant stakeholders (Kalaignanam et al., 2021), creating more valuable marketing insights (Grover et al., 2018).

System adaptability signifies how BDA can adjust to needs and circumstances (Akter et al., 2017). To be competitive, firms must modify their BDA abilities according to technological developments and relevant procedures (Dahiya et al., 2021). Conventional marketing uses a compartmentalized approach that may generate barriers between the users of market intelligence (e.g., the marketing personnel) and those generating insights (e.g., the IT personnel). This makes the firm less adaptable to rapid environmental changes (Kalaignanam et al., 2021). Marketing personnel may be averse to using technologies and algorithms they find difficult to comprehend (Dietvorst et al., 2015). These issues may impact the system adoption capabilities, hindering the adoption of the BDMA insights (Kalaignanum et al., 2021).

System reliability indicates the degree to which the BDA is reliable (Akter et al., 2017). The match between data, tools to be used, and tasks to be performed is critical for the effectiveness of BDA (Ghasemaghaei et al., 2017). Furthermore, the predictive analysis feature of BDA should improve system reliability and, thereby, contribute to the firm's improved performance (Gunasekaran et al., 2018). Extant research has indicated that possessing reliable information causes top-performing companies to be 5.3 to 7.6 times more likely to execute decisions derived from data (Cao & Duan, 2017).

System privacy insinuates the degree to which the BDA system is safe and shields user-specific data (Akter et al., 2017). Legal, ethical, privacy and security considerations play a critical role as firms utilize BD scalable methods (e.g., text and web analytics) that enable them to handle and inspect tracking data (Buhalis & Sinarta, 2019) and data processing methods to attain beneficial information through users' online activities and interactions (Alaei et al., 2019). Accordingly, BD policies must address privacy, security, and liability issues for possible system privacy breaches.

Information Quality

The constant escalation in the amount and speed of accumulation of data allows firms to benefit from BD through the improved market and financial performance, as well as other beneficial outcomes (Ghasemaghaei & Calic, 2019). Information quality may face novel challenges (Clarke, 2015) as BD encompasses new characteristics; thus, the information quality of data becomes more critical (Ghasemaghaei, 2020). The use of data with insufficient quality may lead to poor decision-making, which may negatively contribute to financial and market performance (Hazen et al., 2014).

Information quality can be explained as the completeness, accuracy, format, and currency of the information created in the BDA process. Completeness designates the degree to which the user perceives BDA to deliver the required information. Data should neither include unnecessary information nor lack any relevant data. Unexploited data, which is ignored, may indicate entropy (i.e., lack of order or predictability). It may lead to lower data information quality. It may also present a problem of sustaining data consistency when used in various contexts (Loshin, 2011).

Accuracy concentrates on the precision of the information, indicating the degree to which data values are consistent with a known source of precise information. The potential sources with data (in)accuracy occur from data entry, data integration, system errors, and inaccurate recording by the data source (Gordon & Shankaranarayanan, 2015). Firms assess the accuracy of data by comparing the original data to a baseline or a known correct dataset.

Consistency denotes how the information is offered. It indicates whether data corresponds with its format and structure or is format compliant. BD quality refers to provisional functional dependencies as data quality rules to spot semantic mistakes (Taleb et al., 2015).

Currency signifies the user's perception of the degree to which the information is current (Akter et al., 2017). Currency can measure whether the information is "up-to-date" or correct despite modifications (Loshin, 2011).

The level of deployment may impact all dimensions of the information quality. The accruing experience and learning throughout the deployment process would positively impact information quality (Love et al., 2015; Manley & Chen, 2017). The development process, the ability to organize information, and the alertness to errors will improve with advancing levels of deployment experience with BDMA systems (Ludwick & Doucette, 2009).

Regarding the preceding discussion, this study posits that:

H1: The level of deployment has a significant positive effect on information quality.
H2: The level of deployment significantly positively affects technology quality.

Market Performance

Market performance refers to the functioning of a firm. It can be assessed with sales revenue, profitability, competitive advantage, customer satisfaction, and loyalty (Jayapal & Omar, 2017). This direct reflection of a business's overall performance can be identified through an increase in market share (Chi & Soeck-Jin, 2017). Research has shown that technology has facilitated the development of relationship marketing, improving the relationship between the customer and the firm (Alghamdi & Bach, 2014). The extant research suggests that the technology quality of information systems may positively impact customer orientation and market performance (Zhu & Nakata, 2007).

Information quality in BDMA has been discovered to significantly impact business value, user satisfaction, and overall market performance (Wamba et al., 2018). These are measured through indicators like market entry, new product/service introduction, new product/service success rate, and market share (Wamba & Behaat, 2017). Additionally, marketing performance measures may include customer retention as loyal customers enhance firms' profits. Obtaining new customers can be more expensive than retaining existing customers (Gengeswari & Padmashantini, 2013). Therefore:

H3: Information quality has a significant positive effect on market performance.
H4: Technology quality has a significant positive effect on market performance.

Financial Performance

A study evaluating the impact of system quality, information quality, and service quality on the performance of the firm found that system quality is a factor of organizational performance (Bahari & Mahmud, 2017) measured through profitability, sales, and return on investment (ROI) (Tahir, 2020). Research has described the positive performance impact of the use of BDMA (Germann et al., 2013). A firm's financial sustainability may improve as they recognize that they are data-driven (Kibe et al., 2020). Furthermore, BDMA may lead to more effective marketing and decisions, as firms that assume data-driven routines may contribute to better financial results (Kibe et al., 2020; McAfee & Brynjolfsson, 2012).

The financial performance measures may include indicators like profitability (Harb, 2019), ROI (Naz et al., 2016), and sales growth (Wulandari et al., 2019). The researchers expect that a firm with higher information and technology quality would perform better financially. Therefore, this study posits that:

H5: Information quality has a significant positive effect on financial performance.
H6: Technology quality has a significant positive effect on financial performance.

METHODOLOGY

Sample and Respondent Characteristics

Responses were gathered from marketing professionals with experience in BDMA with the support of SurveyMonkey, a marketing research company. During the winter of 2021, 970 responses were collected from respondents in Canada and the United States. The minimum age of respondents was 18 years. The respondents were financially compensated, consistent with SurveyMonkey policies. The survey instrument was initiated with a qualifying question. The requirement was that the companies were at least in the limited deployment stage of BDMA. The final sample included 236 acceptable responses in stages 5-7 of active BDMA deployment (see Table 1; Murphy & Cox, 2016).

Table 1. *BDMA Deployment Stage in the Companies of the Respondents*

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

Cochran's formula for continuous data was utilized to define the ampleness of the sample size (Cochran, 1977). A sample size of 137 is needed, with an alpha level of 0.025 in each tail at 1.96, the anticipated standard deviation on a five-point scale of 0.8, and a margin of error of 0.15. There were 236 responses; therefore, the sample size can be considered adequate. Recent literature has quantified, regarding the use of PLS-SEM, that with a minimum path coefficient size of 0.11 and a significance level of 5%, a minimum sample size of 155 is needed (Hair et al., 2022). Therefore, the sample size can be deemed adequate based on both criteria.

Measurement and Questionnaire Development

A questionnaire with variables adapted from extant research was developed and used for data collection (see Table 2). The questionnaire concentrated on the constructs and their indicator variables. A five-point response scale (1 = completely disagree; 5 = completely agree) or equivalent was used for all questions except for the level of deployment.

Table 2. *Target Constructs and Indicator Variables (CRA = Cronbach Alpha, CR =Composite Reliability, AVE = Average Variance Extracted)*

Construct	Indicator Variable	Source
System Reliability CRA: 0.74 CR: 0.85 AVE: 0.65	• System operates reliably for marketing analytics. • System performs reliably for marketing analytics. • Operation of the system is dependable for marketing analytics.	Akter et al. (2017)
System Adaptability CRA: 0.73 CR: 0.85 AVE: 0.65	• System can be adapted to meet a variety of marketing analytics needs. • System can adjust to new demands or conditions during marketing analytics. • System is flexible in addressing needs as they arise during the marketing analytics.	
System Integration CRA: 0.78 CR: 0.87 AVE: 0.69	• System effectively integrates data from different areas of the company. • System pulls together data that used to come from different places in the company. • System effectively combines different types of data from all areas of the company.	
System Privacy CRA: 0.74 CR: 0.85 AVE: 0.66	• System protects information on personal issues. • System protects information on personal identity. • System offers a meaningful guarantee that it will not share private information.	
Completeness CRA: 0.73 CR: 0.85 AVE: 0.65	• ____ provides a complete set of information. • ____ produces comprehensive information. • ____ provides all the information needed.	
Currency CRA: 0.77 CR: 0.87 AVE: 0.69	• ____ provides the most recent information. • ____ produces the most current information. • ____ always provides up-to-date information.	
Format CRA: 0.77 CR: 0.87 AVE: 0.68	• Information provided by the marketing analytics is ____ well formatted. • Information provided by the marketing analytics is ____ well laid out. • Information provided by the marketing analytics is ____ clearly presented.	
Accuracy CRA: 0.72 CR: 0.84 AVE: 0.64	• ____ produces correct information. • ____ provides few errors in the information. • ____ provides accurate information.	

Table 2 continued on next page

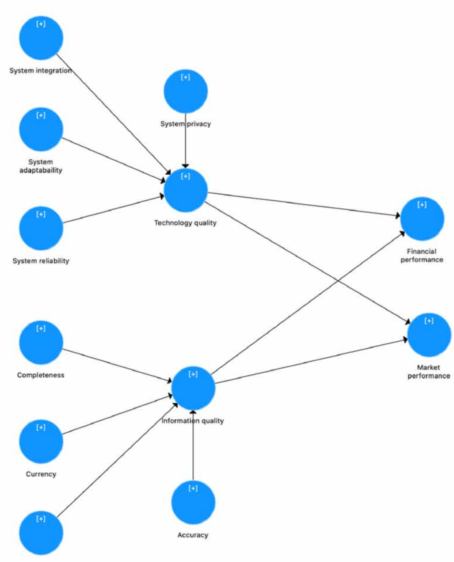
Table 2 continued

Construct	Indicator Variable	Source
Financial Performance CRA: 0.82 CR: 0.88 AVE: 0.65	• Customer retention • Sales growth • Profitability • Return on Investment (ROI)	Germann et al. (2013); Wamba et al. (2017)
Market Performance CRA: 0.82 CR: 0.88 AVE: 0.65	• Our quicker entry to new markets. • Our faster introduction of new products or services to the market. • Our success rate of new products or services has been higher than our competitors. • Our higher market share.	
Level of Deployment	• Unaware of any marketing analytics applications. • Aware of the marketing analytics applications. • Knowledge of the marketing analytics applications but have not yet evaluated any. • Evaluation of potential of the marketing analytics applications. • Limited deployment of the marketing analytics applications. • General deployment indicating wide impact on critical business processes. • Mature deployment for a longer period of time with legacy support.	Murphy and Cox (2016)

Structural Model

The following model was developed based on the literature review (see Figure 1). This model is an explicit illustration of the study's hypotheses.

Figure 1.



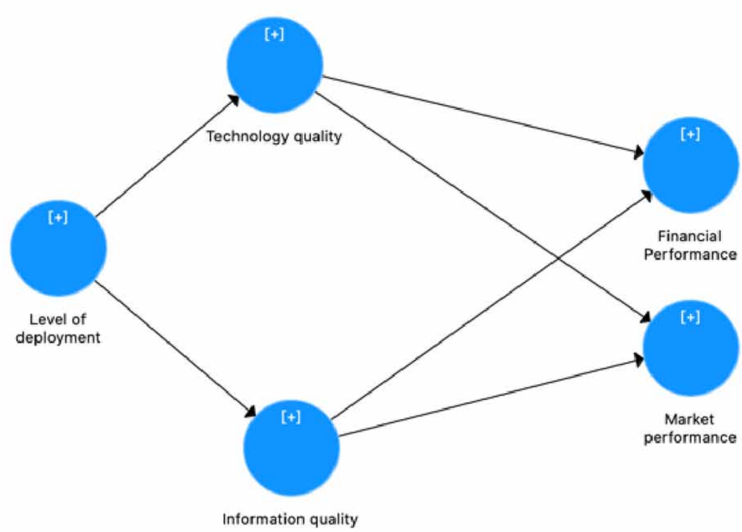
Method of Statistical Analysis

The analysis of the model was done using partial least squares structural equation modelling (PLS-SEM). The two structural equation modelling methods include covariance-based (CB-SEM) and partial least squares (PLS-SEM). These methods' measurement philosophies and goals are dissimilar (Hair et al., 2018). The covariance-based process assesses the variance in a variable shared with other variables (i.e., common variance). The PLS-SEM method uses the indicator variables' total variance. This creates linear combinations of indicator variables to represent the appropriate constructs (Hair et al., 2018). PLS-SEM was chosen because the research aims to predict target constructs and identify key driver constructs. This goal is not related to theory testing or confirmation. Furthermore, the study does not require a global goodness-of-fit criterion, which is necessary for CB-SEM (Hair et al., 2022). Current recommendations on the quality criteria for PLS-SEM were used (Ringle et al., 2018) to evaluate the measurement and structural models.

The structural model uses "higher-order" constructs for technology and information quality. Both are multi-dimensional constructs (see Figure 1). Higher-order constructs enable modelling constructs on both abstract higher-order levels and concrete lower-order measurement dimensions. The use of higher-order constructs reduces the path model relationships under investigation. In addition, it contributes to parsimony. It is important to conceptualize and specify the higher-order constructs using sound measurement theory (Sarstedt et al., 2019). The assessment of the model can be achieved using either repeated indicators or a two-stage approach in the reflective-formative approach. Both produce comparable results when the sample size is large enough (Sarstedt et al., 2019).

The chosen method, the two-stage indicator approach, includes a formative hierarchical latent construct model in an endogenous position (Becker et al., 2012). Therefore, the variance of the higher-order construct will be explained by the lower-order measurement variables (i.e., the R^2 will be 1). Thus, the latent variable score estimates need to be added to the dataset instead of trying to assess the model estimates. Then, in the follow-up analysis, these scores will be utilized as indicators in the higher-order construct measurement model (Sarstedt et al., 2019). Furthermore, the construct "level of deployment" was inserted into the model in this stage (see Figure 2).

Figure 2.



DATA ANALYSIS

Background Data

Table 3 portrays this research's sample population (N = 236). The respondents represented a variety of industry types, including finance and insurance, information and cultural industries, education services, manufacturing, construction, and real estate.

Table 3. *Description of the Sample*

#	Country of residence	N (%)	#	Years with the Organization	N (%)
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**	
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%)

Assessment of the Measurement Model

The first phase evaluated the distinct scales used to compute the various constructs. This started with the assessment of indicator reliability. A bias-corrected and accelerated bootstrapping analysis determined the significance of the indicator variables. All loadings were greater than 0.70; therefore, relationships between the indicator variables and their relevant constructs were also significant (Rosenbusch et al., 2018).

The following phase assesses internal consistency reliability (see Table 5). Literature has indicated that Cronbach's alpha is a conservative measure of reliability. The composite reliability (target for both in-between 0.70 and 0.95) will likely exaggerate the internal consistency reliability. Therefore, the true reliability is in between these two criteria. Cronbach's alpha value is the lower bound, and the composite reliability is the upper bound (Hair et al., 2022). On this basis, the internal consistency reliability is adequate. For convergent validity (generally assessed with the average variance extracted [AVE], the minimum threshold level is 0.50. See Table 2.

The next phase is the evaluation of discriminant validity, which signifies the extent to which a construct differs from other constructs (Hair et al., 2022). This cannot be done using the standard procedure in the case of the higher-order models due to the use of repeated indicators. Extant research indicates that the higher-order component only needs to be assessed as part of the structural model regarding the discriminant validity.

Recent literature suggests the use of Heterotrait-Monotrait (HTMT) of the correlations. This signifies the ratio of the between-trait correlations to the within-trait correlations (Hair et al., 2022). The threshold value of 0.90 should not be exceeded for the HTMT values (Henseler et al., 2015). A significance test should also be performed because the HTMT analysis serves as the basis for the discriminant validity test. However, standard significance tests cannot be used to assess whether the HTMT correlation is significantly different from the value of one as the use of PLS-SEM does not include a distributional assumption. Thus, bootstrapping procedures have been suggested to test the significance (Hair et al., 2022). A bootstrap confidence interval that consists of the value of 1 will indicate a lack of discriminant validity. None of the confidence intervals included the value of 1; thus, discriminant validity has been achieved (despite one of the HTMT values slightly exceeding the threshold value of 0.90).

Assessment of the Structural Model

The structural model assessment is initiated with the collinearity assessment. This signifies the correlation between the exogenous predictors and is usually assessed with the variance inflation factor (VIF). All VIF values in the structural model were below the strict threshold value of three, indicating a lack of collinearity (Hair et al., 2011).

The following phase is the assessment of predictive validity with the R^2 and Stone-Geisser Q^2 values (Geisser, 1974; Stone, 1974) (see Table 4). Research has recognized that R^2 values of 0.75, 0.50, and 0.25 can be explained as substantial, moderate, and weak, respectively. Contemporary research has also determined strength criteria for the Stone-Geisser Q^2 values so that 0.25 and 0.50 values signify medium and large predictive relevance (Hair et al., 2020). Thus, the endogenous constructs of critical financial and market performance have close to substantial predictive relevance and strength.

Table 4. *Predictive Validity and Strength*

Construct	R^2	R^2 Adjusted	Q^2
Financial performance	0.61	0.61	0.60
Information quality	0.05	0.05	0.05
Market performance	0.64	0.64	0.63
Technology quality	0.03	0.02	0.02

Hypotheses Testing

The concluding phase in assessing the structural model is a review of the significance of the path coefficients in the structural model. This coincides with the hypotheses testing in this case (see Table 5).

Extant research indicates that statistical significance is insufficient when recording the research results; therefore, effect size should also show (Cohen, 1992; Kline, 2004). Effect size may be the most notable discovery in the statistical analysis. With a sufficiently large sample size statistical testing can find significant differences that are meaningless in practice when possessing a sufficiently large sample size. Thus, the reporting of the p-values is not sufficient (Sullivan & Feinn, 2012). Previous literature has indicated that the values of 0.02, 0.15, and 0.35 represent the exogenous constructs with small, medium, or large effect sizes, respectively (Hair et al., 2022). Effect size is not affected by sample size; thus, it can be compared between different research studies (Hair et al., 2010).

Table 5. *Significance of the Path Coefficients in the Model in the Whole Data Set*

#	Exogenous construct	Path coefficient	p-value	Hypotheses support	Effect size (f^2)	Effect size description
1	Information quality -> Financial performance	0.373	0.001	Yes	0.06	Medium to small
2	Information quality -> Market performance	0.347	0.006	Yes	0.06	Medium to small
3	Level of deployment -> Information quality	0.225	0.000	Yes	0.05	Medium to small
4	Level of deployment -> Technology quality	0.158	0.015	Yes	0.03	Small
5	Technology quality -> Financial Performance	0.427	0.000	Yes	0.08	Medium to small
6	Technology quality -> Market performance	0.473	0.001	Yes	0.11	Medium to small

DISCUSSION

The objective of this research was to examine the impact of the level of BDMA deployment on technology and information quality, as well as their impact on the market and financial performance in BDMA. The initial sample included 970 responses from Canadian and U.S. respondents, with a minimum age of 18 years. The final sample included 236 responses, with at least a limited level of actual BDMA deployment (see Table 1).

Previous research suggests that firms operating in dynamic business contexts may face changing customer demand, increased competition, and rapid technological advancements (Roberts & Grover, 2012). The inability to react efficiently to these challenges may severely impact the firm's performance. Consequently, when companies face challenges, technology quality (i.e., system reliability, adaptability, integration, and privacy) and information quality (i.e., completeness, currency, format, and accuracy) may aid managers in making better decisions. Additionally, they may have a positive and significant effect on a firm's market and financial performance.

BDMA provides insights to organizations on methods that benefit from the BD they generate, collect, or consume for marketing purposes (Frizzo-Barker et al., 2016). When firms adopt a data-driven approach, they expect to achieve better overall firm performance and meet their marketing objectives (McAfee & Brynjolfsson, 2012). The results of this research support this claim. Market performance in this research was measured with quick entry to new markets, faster introduction of new products, the success of new products or services compared to competitors, and higher market share. These significantly and positively contributed to market performance consistent with previous research (Ji-fan Ren et al., 2017). On the other hand, financial performance was measured with customer retention, sales growth, profitability, and ROI. These all contributed to financial performance, consistent with previous research (Germann et al., 2013; Ren et al., 2017).

Extant research has devoted limited consideration to the determinants of BDMA's impacts on firms' financial and market performance, especially when looking at the situation from a marketing point of view. The samples in previous studies included: business analysts in engineering master's programs at Chinese universities (Ji-fan Ren et al., 2017); managers in small-to-medium enterprises (Maroufkhani et al., 2020); BD analysts in the U.S. and France (Akter et al., 2017); business analysts and IT managers with analytics experience in France (Wamba & Akter, 2019); business analysts, BD analytics, and IT professionals (Akter, 2016); business and IT executives (Corte-Real et al., 2019); chief information officers (Garmaki et al., 2016; Raguseo & Vitari, 2017); and senior executives

(Germann et al., 2013). They did not include marketing personnel (although they were the primary users of the information gained from BDMA).

The results of this study indicate that technology and information quality positively contribute to both financial and market performance. There is, therefore, support for the perspective that there is a need to focus on the technology and information quality of BDMA. These results indicate a degree of consistency with previous research. For example, Ji-fan Ren (2017) discovered a positive and significant relationship between system quality/information quality and perceived business value. Additionally, the study showed that the impact of system quality on firm performance (as a function of financial and market performance) was positive and significant. Still, the relationship between information quality and firm performance was not. However, the results could not sufficiently explain this phenomenon. Notably, the sample consisted of business analysts in engineering master programs at Chinese universities.

Extant research has paid scarce attention to the impact of the level of deployment of the BDMA systems, especially from a marketing perspective. The level of deployment ranged in this research from complete unawareness to awareness, knowledge, evaluation, limited deployment, general deployment, and mature deployment of the BDMA systems (Murphy & Cox, 2016). The first three levels were omitted from the data set. The results indicated a positive and significant relationship between the level of deployment and information quality, as well as the level of deployment and technology quality.

Germann et al. (2013) is a noteworthy exception to the relative lack of research about the level of deployment. The context of the study by Germann et al. (2013) was marketing analytics (not BDMA), the measurement of performance was done with financial performance measures only (total sales growth, profit, and ROI), not including market performance measures, and the measurement of the level of deployment was done somewhat differently in comparison to this study. It was done with three questions (range of 1-7); however, the mean value (or distribution) of the level of deployment still needs to be revealed. The focal variable "deployment" histogram indicated a range of values. The level of deployment of marketing analytics may have been somewhat lower in the Germann et al. (2013) study than in this study. Despite the differences between these two studies, the results on the level of deployment were consistent with the findings of Germann et al. (2013).

IMPLICATIONS

Studies have examined BD from many organizational viewpoints, with little attention paid to the marketing perspective. BDMA requires investments in technology and information quality, which enhances the ability to capture, manage, and process enormous amounts of marketing data from several sources in a fast and reliable manner. Essential elements of gaining value from BDMA include recruiting people with an advanced analytical understanding of BD and marketing skills, as this fosters organizational learning in marketing and embedding BD decision-making into the marketing decision making (Zheng & Bender, 2019). Adopting BDMA requires the implementation of multiple dimensions of technology and information quality supported by management commitment. The findings indicate that the technology and information quality aspects of BD aid BDMA and contribute to a firm's financial and market performance. Furthermore, the deployment level also positively impacts the technology and information quality in BDMA.

Overall, this discussion highlights the significance of technology and information quality resources and their holistic use. While obtaining technology and information resources is a crucial first step in BDMA, it is only one part of an arduous process in which the quality of the information must be ensured in its completeness, currency, format, and accuracy. Furthermore, the data's privacy, reliability, and adaptability must be ensured, along with guaranteeing that it is well-integrated for relevant stakeholders. This illustrates that firms must commit to investing in BD to gain its highest value. The introduction of BD must be comprehensive about aspects like information, technology, personnel, communication, and training. Conversely, applying BD requires a total firm commitment, which is more than just a process. It must be embedded into the firm and its culture.

LIMITATIONS AND FUTURE RESEARCH

The impacts of BDMA have been discussed in this study; however, it has a few limitations. The sample was gathered from Canadian and U.S. marketing managers. Thus, the geographical scope is limited. However, the North American BD market is the largest in the world (Allied Market Research, 2021; Srivastava, 2019). Additionally, the assessment of the level of deployment used only one variable. Using more variables to measure the level of deployment (like Germann et al. [2013]) may be warranted.

Furthermore, the measures for assessing financial and market performance were perceptual rather than objective. Therefore, coming up with objective criteria for determining financial and market performance would be valuable. Nonetheless, the findings of this research are helpful for marketing academics and practitioners, mainly as the research in this field has been limited.

CONCLUSION

BDMA helps firms attain a competitive advantage and exploit untapped marketing opportunities. Firms will have a competitive advantage as they can make faster, more knowledgeable decisions when using BDMA. BD is collected using automated means from a myriad of input sources; therefore, there is a possibility that the data could be faulty or contain errors.

The objective of this study was to examine the effect of technology and information quality on the market and financial performance in the context of BDMA. It explored the role of the level of deployment toward technology and information quality. Firms can attain a competitive advantage when BD has a level of quality after being processed. Through BDMA, firms may be able to improve sales and leads data, optimize marketing campaigns, enhance customer loyalty, and provide insights into the sales cycle. Also, CRM systems can be enhanced to improve conversion rates, management of new prospects, and CLV. Firms must ensure that they analyze the BD efficiently because the ability to analyze BD thoroughly is the aspect that differentiates successful companies. This research confirms that technology and information quality are vital in enhancing firm performance in a BD environment.

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