The impact of perceived knowledge on marketing agility in the context of big data: role of deployment level

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Abstract

Purpose – Against the backdrop of dynamic capabilities theory, this research examines the relationship between knowledge and marketing agility in the context of big data marketing analytics (BDMA). The relevant knowledge constructs under investigation are business/marketing, relational, technological and technology management. The level of BDMA deployment is also examined to determine its impact on these relationships.

Design/methodology/approach – A survey was used to gather data from marketing professionals working in firms with at least limited experience in big data (BD) deployment in the United States and Canada. The results were analyzed using partial least squares structural equation modeling (PLS-SEM) with a sample of 236 responses.

Findings – The results indicate that marketing professionals perceived the knowledge and marketing agility constructs differently than the previous research on IT professionals. The knowledge construct was perceived as a two-dimensional construct consisting of broad knowledge skills and specific technical knowledge skills. Only the broad knowledge skills construct was significantly related to the marketing agility construct, with progressively high predictive validity and relevance when the deployment of BDMA progresses.

Originality/value – The paper's originality stems from the different conceptualizations of the knowledge and marketing agility constructs due to the use of a novel sample of marketing professionals in this study. The research also contributes to the dynamic capabilities theory by emphasizing the critical role of vital knowledge when aiming to enhance marketing agility.

Keywords Big data marketing analytics (BDMA), Knowledge, Deployment, Marketing agility

Paper type Research paper

Introduction

Firms are expected to benefit from new sources of information with innovative information technologies (IT) to keep up with fast-changing market demands. Exploiting new data with ground-breaking IT may give the firm a competitive advantage, making its marketing operations more efficient and agile. During the last decade, big data (BD) has become one of the most critical aspects for leading firms (Mikalef *et al.*, 2017). Immense volumes of data are being produced daily, meaning that firms may not be capable of extracting relevant and

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eloquent insights from it with their legacy IT and analytical techniques (Kitchin, 2014; Yahoo Finance, 2022). However, when done well, BDMA is often the source for developing meaningful consumer insights by strengthening the firm's real-time marketing decision-making capability (van Auken, 2015).

Firms have begun to accept big data marketing analytics (BDMA) as a bona fide tool for collecting, examining, and locating hidden data patterns (Marjani *et al.*, 2017). BD refers to a vast but heterogeneous amount of data that includes information in different quantities and formats (Sivarajah *et al.*, 2017). It supports the effective creation of digitalized marketing processes and the execution of marketing decisions (Lies, 2019). In addition, BD can help firms to learn about their operational inefficiencies (Naganathan, 2018) and become more agile with their current available resources (Tarn and Wang, 2022).

Integrating BDMA into business processes provides awareness of the marketplace and allows them to proactively shape their marketing responses (Overgoor *et al.*, 2019). Firms must possess automatic, analytical, adaptive, and agile responses to market opportunities (Vera-Baquero *et al.*, 2015; Vossen, 2014). In the context of this paper, "*marketing agility refers to the extent to which an entity rapidly iterates between making sense of the market and executing marketing decisions to adapt to the market*" (Kalaignanam *et al.*, 2021). To do this, firms must have a real-time system to track changes in the marketplace. Firms innovate products, services, channels, and the segmentation of their markets while constantly refining and redefining their marketing processes. Utilizing the business/marketing, relational, technical, and technology management knowledge needed to take advantage of BD, marketing agility can be fostered and catalyze firms to innovate, thereby continuously achieving a competitive advantage.

Knowledge refers to the facts, information, and skills acquired through experience or education (Merriam-Webster, 2023). On the other hand, perceived knowledge is the self-assessment of how much one thinks one knows about the relevant information (Kosnin *et al.*, 2019). An individual's perceived knowledge can affect their behavior through increased self-efficacy (Tamjidyamcholo *et al.*, 2013), which is their belief in their ability to achieve a desired or intended result. Individuals' judgment of their ability to control circumstances is decisive in managing their actions, and self-efficacy is crucial in initiating positive behavior change (Abdulrahman *et al.*, 2022). After all, if we don't feel capable of making our situation/strategy better, why would we try? Moreover, previous research has shown that knowledge positively impacts self-confidence, which positively impacts actual behavior, and knowledge also directly and positively impacts actual behavior (Ramalho and Forte, 2019) and knowledge management (Tamara Keszey, 2018).

Based on the above, a claim can be made that information and (perceived) knowledge positively impact the firm's marketing practices. Therefore, it is unsurprising that marketing practitioners should possess relevant information and knowledge when executing marketing planning and decision-making (Brady *et al.*, 2008). Previous research has investigated the impact of the quality of BDMA on the market and financial performance and discovered a positive and significant impact (Haverila *et al.*, 2022). However, what needs to be found is the collaborative impact of knowledge – whether technical, technology management, business/marketing, or relational, on the marketing agility of the firm in the context of BDMA. As marketing agility is becoming increasingly important in the fast-paced global economy (Gomes *et al.*, 2020; Kalaignanam *et al.*, 2021), understanding the role of knowledge in achieving marketing agility is crucial.

The specific objectives of the research are, first, to examine the dimensionality of the knowledge and agility constructs, as it is feasible to assume that the perceptions of the marketing personnel differ from the perceptions of business analysts, BD analytics, and IT professionals regarding the knowledge construct (Akter *et al.*, 2016) and the perceptions of the managers in the case of the agility construct (Zhou *et al.*, 2019). After all, previous research has examined the dimensionality of constructs and found that discrepancies can exist in constructs such as trust (Poortinga and Pidgeon, 2003), bargaining and persuasion (Su *et al.*, 2019), and customer satisfaction (Khan *et al.*, 2009), among others. These differences in dimensionality may be due to cultural differences among the samples, which may cause construct validity and reliability issues (Andrews, 1989). Consequently, this may make comparisons across populations more challenging, and deductions may be based on the combined data of diverse people instead (Davidov *et al.*, 2014). At the minimum, the lack of similarity in the dimensionality of the constructs may cause an absence of measurement invariance. However, it is essential to understand the dimensionality of these constructs in the BDMA construct for marketing professionals so that we can be more accurate in measuring them in the future. Second, based on the literature review and subsequent EFA, a new structural model to understand how to increase agility based on BDMA will be created. The deployment level may influence marketing professionals' self-efficacy when implementing their BDMA system, so the level of deployment is also examined to determine how it impacts the relationship between knowledge and marketing agility in the context of BDMA.

Literature review

Big data marketing analytics

Big Data (BD) is characterized by volume, velocity, variety, variability, veracity, visualization, and value (Moore, 2023). Essentially, BD relies on a large amount of information that is collected in real-time from a wide variety of sources. While all firms produce data, managing, analyzing, and obtaining beneficial insights from the data using legacy methods is often challenging – new collection procedures, software, and personnel are required to utilize BD to its greatest effect. Managing data necessitates proficiency in mining and filtering the hidden patterns in the data to retrieve valuable information for the firms (Bose, 2009). In this process, firms often depend on analytics, which is the "*process of understanding the data by creating and distributing reports, building, and deploying statistical and data-mining models, exploring and visualizing data, sense-making and other related techniques*" (Chen *et al.*, 2012; Grossman and Siegel, 2014).

The benefits of leveraging data in the marketing context include better decision-making, improved sales activities, enhanced customer journey throughout the pre-purchase, purchase and post-purchase stages, new ways of marketing, risk management and assessment, and support for digital marketing operations. Therefore, it is not surprising that 72% of the respondents in the survey conducted by Harvard Business Review indicated a profitability increase when investing in Big Data Analytics (BDA) (Nico *et al.*, 2021). Well-managed and comprehended BDMA presents an immense marketing opportunity to achieve a competitive advantage for firms and enhances the firm's chances to be more agile.

Marketing agility

The last few years have exposed the ambiguous global economy (e.g. due to COVID-19 and the relevant supply chain issues), which means firms must build sustainable business models resilient to external surprises. Firms have had difficulties adjusting to the implications of the ongoing COVID-19 pandemic that began in 2020 and the Russian war against Ukraine that started in 2022. In adapting to these challenges, firms should be agile in their marketing operations and have the vital knowledge, resources and human capital to react to the challenges and exploit emerging opportunities. When aiming to alleviate the influence of external shocks, agility is crucial, and strategies can be developed to promptly confront these intricate difficulties (Linkov and Trump, 2019).

Based on the dynamic capabilities theory (Teece, 2007), marketing agility (which is a dynamic capability) is vital to a firm's innovation capability (which is an ordinary capability) in current business environments (Foltean and van Bruggen, 2022). Previous research discovered a significant relationship between knowledge acquisition, creation, and application processes and organizational agility (Cegarra-Navarro *et al.*, 2016; Trzcielinski, 2015). It should also be noted that marketing agility and its reliance on knowledge depend on the nature of the market. In reasonably dynamic markets, market agility relies heavily on existing knowledge. In contrast, in high-velocity markets where change is nonlinear and less foreseeable, more prompt and situational new knowledge may be required (Eisenhardt and Martin, 2000).

Unsurprisingly, previous research has found that marketing agility significantly impacts a firm's financial performance in that there is a direct and indirect (through innovation capability) impact on financial performance moderated by market turbulence (Zhou *et al.*, 2019). As firms encounter severe competition and disruptions due to the environmental challenges in the current global economy, it is progressively indefensible to ignore marketing agility initiatives. Therefore, it is essential to investigate the knowledge requirements behind marketing agility.

To be agile in the marketplace, firms need to have the necessary business and marketing knowledge about the current climate of the external environment and the technical knowledge coupled with the technology management knowledge to take advantage of the vast and constantly growing BD. To bring these all together, relational knowledge (see the definition below in the appropriate section) is needed to plan and organize BD projects in a collaborative environment with other relevant actors and entities to maintain excellent customer and internal relationships (Akter *et al.*, 2016; Garmaki *et al.*, 2016). Thus, these variables are discussed in the current paper as predictors of marketing agility. However, the present paper is interested in how the level of deployment influences these relationships, so this variable is discussed first.

Level of deployment

Prior research has deliberated the impact of the level of deployment in the context of information systems. At the individual level, adopting new technology using the technology acceptance model (TAM) as a framework is much more straightforward than adopting new technologies at the organizational level. At the managerial level, the adoption usually proceeds in multiple stages, which may include going back and forth between the stages. As BD applications and knowledge extraction can be rather complex, learning relevant knowledge can be challenging (Sun *et al.*, 2018). Murphy and Cox (2016) have suggested a seven-stage model describing the organizational adoption of information systems, including unawareness, awareness, knowledge, evaluation, limited deployment, general deployment and mature deployment. The last three stages are the adopter stages, and the first four are the non-adopter stages. This model will be used as the framework for the deployment in this research paper. It can be assumed that the usage of various BDMA functionalities increases when the marketing analytics personnel learn more about the available possibilities when proceeding to the more advanced stages of BDMA deployment (Najmul Islam *et al.*, 2020). Thus, higher levels of deployment/adoption may note different effects of the various types of knowledge.

Dynamic capabilities theory

Teece and Linden (2017) first discussed dynamic capabilities theory. Per these authors, an organization must constantly adapt to emerging challenges by ensuring employees can learn and build new strategic assets, integrate these new assets into the firm's existing processes, and transform out-of-date or depreciated assets (Teece *et al.*, 1997). Essentially, it delineates the difference between the firm's skills that make it capable of competing today vs the capabilities that enable it to adapt. The authors have discussed combining dynamic capabilities with reasonable strategies to build a sustainable competitive advantage (Teece, 2014).

BDMA is congruent with the dynamic capabilities theory. BD is constantly evolving, like dynamic capabilities. Furthermore, it predicts future trends and allows decision-makers to quickly anticipate opportunities and threats to adapt to changing marketplaces (Shankar and Gupta, 2024). Unfortunately, dynamic capabilities theory has very few predictions to offer – but the theory does state that higher levels of dynamic capabilities (and personnel's ability to utilize and adapt to new tools) will foster more outstanding strategic prowess. Thus, the different knowledge types will likely lead to greater agility, which will be discussed next.

Business and marketing knowledge

The research on marketing's impact on firm performance has gathered extensive attention as it helps firms boost sales, maintain and build a company image, provide market insights, and create customer value (Krasnikov and Jayachandran, 2008; Markovitch *et al.*, 2020). An innovative marketing strategy positions the firm uniquely against imitation by competitors.

Business and marketing knowledge is required to plan agile marketing strategies (Moi *et al.*, 2019). Here, taking advantage of BD is crucial. Previous research has noted that to achieve marketing agility, the firm needs an organizational structure enabling knowledge-sharing and integration (Kalaignanam *et al.*, 2021). In other words, it is not enough to possess business and marketing knowledge; it also needs to be shared and integrated into the marketing processes of the firm. Here, a reference can be made to the legacy concept of market orientation, which has been defined as follows: "*Market orientation is defined as the organization-wide generation of market intelligence about current and future customer needs, dissemination of intelligence across departments, and organization-wide responsiveness to it*" (Jaworski and Kohli, 1996; Kohli and Jaworski, 1990). One could also claim that the antecedents for market orientation in this definition also apply to marketing agility at the three levels of BDMA deployment (Cegarra-Navarro *et al.*, 2016; Trzcielinski, 2015). Prior research, however, is relatively scarce on the impact of business/marketing knowledge on marketing agility. Based on the above, the following hypotheses are set:

H1a. Business/marketing knowledge positively and significantly impacts the marketing agility of the firms at the limited deployment level of BDMA.

H1b. Business/marketing knowledge positively and significantly impacts the marketing agility of the firms at the general deployment level of BDMA.

H1c. Business/marketing knowledge positively and significantly impacts the marketing agility of the firms at the mature deployment level of BDMA.

Technology management knowledge

Practitioner and academic interest in managing technology efficiently is growing as the complexity and cost of technological innovation increase. Emerging technologies, such as artificial intelligence, social media marketing, BDA, and augmented and virtual reality, provide significant opportunities for enabling innovation, profit, and social impact – and are the key drivers for sustainable business growth (Yawised *et al.*, 2022).

With technological advances in information technology, a business can arrange processes, manage resources, and improve its supply chain and marketing processes.

According to Merriam-Webster, technology can be defined as "*the application of scientific knowledge for practical purposes, especially in industry* " (Merriam-Webster, 2023). Technology management has been frequently identified as a dynamic capability of firms (Cetindamar *et al.*, 2009).It is "*the effective identification, selection, acquisition, development, exploitation, and protection of technologies needed to preserve a stream of new products and services to the market*" (Phaal *et al.*, 2006). Information technology management directly impacts critical company functions such as strategic planning, innovation, new product development, project management and marketing. Furthermore, technology management is essential for firms operating globally, as competition in global markets is more intense (Kvedarienė, 2019).

In supply chain management, previous research has discovered a significant relationship between supply chain analytics capability and supply chain agility (Fosso Wamba and Akter, 2019). To be able to use the capabilities efficiently, relevant knowledge is needed. Previous research has indicated that information technology management practices may impact customer service (Karimi *et al.*, 2001), digital marketing (Badawy, 2009), agile capabilities (Ansari *et al.*, 2024), and supply chain agility (Mandal, 2018). Previous research has not, however, examined the impact of technology management knowledge on marketing agility. It is realistic to assume that the effect mentioned above also applies to marketing agility at the limited, general and mature levels of deployment of BDMA, which leads to the following hypotheses:

H2a. Technology management positively and significantly impacts the marketing agility of the firms at the limited deployment level of BDMA.

H2b. Technology management positively and significantly impacts the marketing agility of the firms at the general deployment level of BDMA.

H2c. Technology management positively and significantly impacts the marketing agility of the firms at the mature deployment level of BDMA.

Technical knowledge

Technical knowledge affects economic growth (Kim and Lee, 2015). The possession and implementation of technical knowledge, which refers to knowledge about technical features, incorporating operational systems, statistics applications, programming languages (e.g. C+) and database management systems (e.g. Oracle) (Akter *et al.*, 2016) regarding the implementation of BDMA can be a differentiating factor among firms. They can result in an advantageous market position. Also, firms with better utilization of technical knowledge can increase their productivity in marketing operations. Firms with technical knowledge may also be better positioned to identify market opportunities and improve customer benefits (Kim and Lee, 2015). Technical knowledge and capabilities from BD initiatives are required to achieve desired organizational outcomes (Walls and Barnard, 2020) and market performance (Gupta and George, 2016). Earlier research has not, however, inspected the impact of technical knowledge on marketing agility. Based on the discussion above, it is reasonable to assume that technical knowledge has a positive and significant impact on marketing agility at the limited, general, and mature levels of deployment of BDMA, which leads to the following hypotheses:

H3a. Technical knowledge positively and significantly impacts the marketing agility of the firms at the limited deployment level of BDMA.

H3b. Technical knowledge positively and significantly impacts the marketing agility of the firms at the general deployment level of BDMA.

H3c. Technical knowledge positively and significantly impacts the marketing agility of the firms at the mature deployment level of BDMA.

Relational knowledge

Technical, technology management, and business and marketing knowledge need to be high when marketing communication increases. Therefore, relational knowledge, which refers to the ability of analytics professionals to communicate and work with people from other entities and business functions, may also be required to succeed when aiming for enhanced marketing agility (Akter *et al.*, 2016). Thus, cross-functional collaboration using information is necessary.

Based on the above, the organizational structure should enable lateral communication between relevant organizational units, reduce conflicts, and allow sensemaking of the critical BD. In learning, relational knowledge has been considered a higher cognitive process as it gives better perspectives, incorporates real-world knowledge, and constructs mental models that reflect the logical consequences of insights (Halford *et al.*, 2010). Former research, however, is still being determined regarding the impact of relational knowledge on marketing agility. Accordingly, this leads to the following hypotheses:

H4a. Relational knowledge positively and significantly impacts the marketing agility of the firms at the limited deployment level of BDMA.

H4b. Relational knowledge positively and significantly impacts the marketing agility of the firms at the general deployment level of BDMA.

H4c. Relational knowledge positively and significantly impacts the marketing agility of the firms at the mature deployment level of BDMA.

Methodology

Sample and respondent characteristics

Responses from marketing professionals with experience in BDMA were gathered with the help of the SurveyMonkey marketing research company (SurveyMonkey, 2024). Nine hundred seventy responses were collected from Canadian and U.S. respondents at least 18 years old. The respondents were financially compensated in a manner consistent with SurveyMonkey policies. The survey began with a qualification question, as the companies the respondents worked for needed to be at least in the limited deployment stage regarding BDMA (see Table 1). This decision was made based on the assumption that the responses of

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

Source(s): Table by authors'

Table 1. BDMA deployment stage in the respondents' companies

participants working in firms that have or have not adopted BDA may differ significantly (e.g. Brown, 2014; Ma and Lee, 2020; Wolverton and Cenfetelli, 2019)– and we wanted the respondents to have at least some experience in implementing a BDMA program so that they had first-hand knowledge to draw upon. After all, previous research has examined the impact of experience and discovered that experience might impact attitudes and behavioral intentions when using the technology acceptance model (TAM) as the theoretical framework (Bhardwaj and Aggarwal, 2017; Unal and Uzun, 2021). Overall, the final sample included 236 acceptable responses in various stages of active BDMA deployment.

Cochran's continuous data method was applied to establish the suitability of the sample size (Cochran, 1977; Kanaki and Kalogiannakis, 2023). With an alpha level of 0.025 in each tail of 1.96, an anticipated standard deviation on a 5-point scale of 0.8, and a conventional margin of error of 0.15, a sample size of 137 was required. To assess the adequacy of the sample size for using PLS-SEM, literature has quantified that to get a minimum path coefficient level of 0.21 and a desired significance level of 5%, a sample size of 69 is required (Hair *et al.*, 2022), which is consistent with the inverse square root method (Kock and Hadaya, 2018). Therefore, the sample size is acceptable based on these benchmarks.

Measurement and questionnaire development

The researchers developed a survey questionnaire to gather data about the central constructs and their indicator variables. The items for the survey were adapted from existing literature and were measured on a 5-point Likert scale (Likert, 1936) (where 1 = Completely disagree, 5 = Completely agree) (see Table 2).

Structural model

The literature review established the structural model (Figure 1). This model is a graphic representation of the hypotheses developed for the current study.

Method of statistical analysis

The factorial invariance was analyzed using an exploratory factor analysis (EFA). The model was analyzed using partial least squares structural equation modeling (PLS-SEM). There are two alternative methods of structural equation modeling: covariance-based (CB-SEM) and partial least squares (PLS-SEM). The measurement philosophies and goals of the analysis differ between these methods. The covariance-based method contemplates the variance in a variable shared with other variables (i.e. common variance) (Dash and Paul, 2021).

Meanwhile, PLS-SEM uses the indicator variables' total variance to create linear combinations of indicator variables to denote the relevant constructs (Dash and Paul, 2021). PLS-SEM was selected for the current paper as the research goal is to predict key target constructs and identify key driver constructs. It is not related to theory testing or confirmation (Hair *et al.*, 2019). Furthermore, the research does not require a global goodness-of-fit criterion, which would be necessary for CB-SEM. Up-to-date guidelines for PLS-SEM were followed to assess the measurement and structural models (Usakli and Rasoolimanesh, 2023).

Data analysis

Background data

Table 3 provides the descriptive statistics of the sample population in this research. The respondents represented a variety of industry types, including marketing professionals working for businesses in finance and insurance, information and cultural industries, education services, manufacturing, construction, and real estate, among others. Table 4 presents the mean values and standard deviations of the measurement variables.

Assessing the dimensionality of the exogenous and endogenous constructs

Before evaluating the quality of the measurement and structural models, the dimensionality of the exogenous and endogenous constructs (i.e. the factorial invariance) was examined separately, as advised in the literature (Hair *et al.*, 2010). Previous research has indicated marketing agility as a four-dimensional construct of proactiveness, responsiveness, flexibility, and speed (Haverila *et al.*, 2024; Zhou *et al.*, 2019). The exploratory factor analysis (EFA) of the endogenous construct of marketing agility determined that the construct was one-dimensional (variance explained 52.7%). All factor loadings exceeded the value of 0.50, meaning removing any variables from the factor solution was unnecessary. The communality values were evaluated with a threshold level of 0.50 (Hair *et al.*, 2010). A communality value under 0.50 indicates that less than half of the variance has been considered in recognizing the latent construct. It is essential to state, however, that the

Construct	Indicator variable	Source
Technical knowledge	1. Analytics personnel are very capable in terms of programming skills 2. Analytics personnel are very capable in terms of managing project life cycles 3. Analytics personnel are very capable in the areas of data and network management and maintenance 4. Analytics personnel create very capable decision support systems	Akter *et al.* (2016) Garmaki *et al.* (2016)
Technology management knowledge	1. Analytics personnel show superior understanding of technological trends 2. Analytics personnel show superior ability to learn new technologies 3. Analytics personnel are very knowledgeable about the critical factors for the success of our organization 4. Analytics personnel are very knowledgeable about the role of business analytics as a means, not an end	
Business/marketing knowledge	1. Analytics personnel understand our organization's policies and plan at a very high level 2. Analytics personnel are very capable of interpreting business/marketing problems and developing appropriate technical solutions 3. Analytics personnel are very knowledgeable about our marketing objectives 4. Analytics personnel are very knowledgeable about the business environment	
Relational knowledge	1. Analytics personnel are very capable in terms of planning, organizing and leading projects 2. Analytics personnel are very capable in terms of planning and executing work in a collective environment 3. Analytics personnel are very capable in terms of teaching others 4. Analytics personnel work very closely with customers and maintain productive user/client relationships	

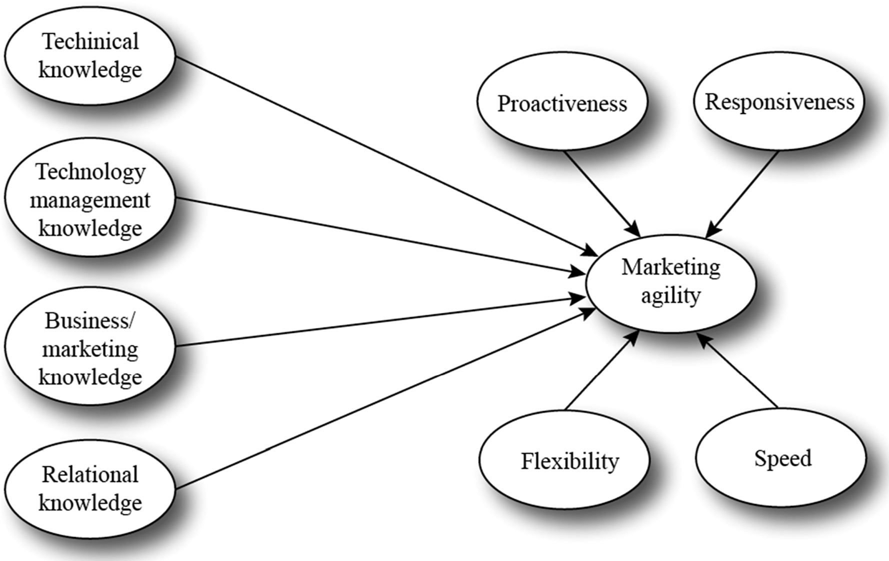
(*continued*)

Table 2. Measurement of the target constructs

Construct	Indicator variable	Source
Marketing agility: proactiveness	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	Zhou *et al.* (2019)
Marketing agility: responsiveness	1. We can respond to changes in demand without overstocking or losing sales 2. We can respond quickly to supply volume fluctuations by having suppliers in many regions of the world 3. When an unexpected threat emerges, we are able to adjust through resource reconfiguration 4. We can react to fundamental changes with respect to changing the competitor landscape	
Marketing agility: flexibility	1. We can market a wide variety of products within our portfolio 2. We can offer different products through minor modifications to existing ones 3. We can adjust what we offer to match market needs	
Marketing agility: speed	1. We can meet customer's changing needs faster than our competitors 2. We compress time from product concept to marketing to respond quickly to the changes in customer needs 3. We can quickly change our product mix in response to changing market opportunities 4. We are fast at changing activities that do not lead to the desired effects	

Source(s): Table by authors'

Table 2.



Source(s): Figure by authors'

Figure 1.
The initial structural model for the study

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

Source(s): Table by authors'

Table 3. Description of the sample (N = 236)

communalities must be interpreted in the context of the interpretability of the factor solution (Fabrigar *et al.*, 1999; Hair *et al.*, 2010). All communality values exceeded the value of 0.40, and as they all logically belonged to the same factor, none were removed from further analysis.

The results of the EFA on the exogenous variable data set can be seen in Table 5. Please refer to Table 2 regarding the wording of the variables. Again, all loadings exceeded the threshold level of 0.50. There were no cross-loadings in the EFA solution, and the solution explained 52.5% of the total variance. The naming was done based on the variable loadings in the EFA solution. Based on the EFAs performed, a modified structural model was created (see Figure 2). Again, all communality values exceeded the value of 0.40. As all of them logically belonged to the factor solution (Fabrigar *et al.*, 1999; Hair *et al.*, 2010), none were removed from further analysis.

Assessment of the measurement model

The first step was to assess the individual scales used to measure the various constructs. The assessment of the measurement model starts with an evaluation of the indicators' reliability. A bias-corrected and accelerated bootstrapping analysis was conducted to determine the significance of the indicator variables. The results can be seen in Table 4, revealing that all

Table 4. Mean values, standard deviations, loadings, and bias-corrected confidence intervals (BCCI) of the variables

Final construct	Original construct	Indicator variable	Mean	Std. dev	Outer load	BCCI 2.5%	BCCI 97.5%
Technical knowledge	Technical knowledge	1. Analytics personnel are very capable in terms of programming skills	3.91	1.05	0.84	0.77	0.88
		2. Analytics personnel are very capable in terms of managing project life cycles	3.77	1.10	0.76	0.69	0.82
		3. Analytics personnel are very capable in the areas of data and network management and maintenance	3.86	1.07	0.87	0.83	0.91
		4. Analytics personnel create very capable decision support systems	3.94	0.96	0.77	0.69	0.83
Technology management knowledge	Technology management knowledge	1. Analytics personnel show superior understanding of technological trends	4.00	0.92	0.69	0.60	0.76
		2. Analytics personnel show superior ability to learn new technologies	3.95	0.97	0.76	0.69	0.81
		3. Analytics personnel are very knowledgeable about the critical factors for the success of our organization	3.84	1.05	0.74	0.68	0.80
		4. Analytics personnel are very knowledgeable about the role of business analytics as a means, not an end	3.83	1.07	0.74	0.67	0.81
Business/marketing knowledge	Business/Marketing knowledge	1. Analytics personnel understand our organization's policies and plan at a very high level	3.83	1.06	0.71	0.64	0.78
		2. Analytics personnel are very capable of interpreting business/marketing problems and developing appropriate technical solutions	3.75	1.13	0.74	0.67	0.80
		3. Analytics personnel are very knowledgeable about our marketing objectives	3.84	1.08	0.76	0.70	0.81
		4. Analytics personnel are very knowledgeable about the business environment	3.84	0.98	0.69	0.60	0.77

(*continued*)

Table 4.

Final construct	Original construct	Indicator variable	Mean	Std. dev	Outer load	BCCI 2.5%	BCCI 97.5%
Relational knowledge	Relational knowledge	1. Analytics personnel are very capable in terms of planning, organizing and leading projects	3.93	1.02	0.72	0.65	0.78
		2. Analytics personnel are very capable in terms of planning and executing work in a collective environment	3.79	1.11	0.75	0.69	0.80
		3. Analytics personnel are very capable in terms of teaching others	3.82	1.04	0.84	0.79	0.88
		4. Analytics personnel work very closely with customers and maintain productive user/client relationships	3.87	1.02	0.69	0.60	0.76
Marketing agility	Marketing agility: Proactiveness	1. We can spot the first indicators of new market threats	3.82	1.01	0.71	0.63	0.79
		2. We are often the first to seize new market opportunities	3.77	1.06	0.72	0.65	0.78
		3. We can anticipate new opportunities for market growth	3.72	1.06	0.72	0.65	0.78
		4. We create new preferences by informing customers about new benefits of our products	3.73	1.03	0.75	0.68	0.81
	Marketing agility: Responsiveness	5. We can respond to changes in demand without overstocking or losing sales	3.78	1.05	0.73	0.65	0.79
		6. We can respond quickly to supply volume fluctuations by having suppliers in many regions of the world	3.72	1.08	0.72	0.65	0.79
		7. When an unexpected threat emerges, we are able to adjust through resource reconfiguration	3.71	1.08	0.73	0.66	0.79
		8. We can react to fundamental changes with respect to changing the competitor landscape	3.78	1.12	0.72	0.65	0.79
	Marketing agility: Flexibility	9. We can market a wide variety of products within our portfolio	3.68	1.19	0.72	0.64	0.79
		10. We can offer different products through minor modifications to existing ones	3.83	1.05	0.71	0.64	0.78
		11. We can adjust what we offer to match market needs	3.68	1.13	0.76	0.69	0.81
	Marketing agility: Speed	12. We can meet customer's changing needs faster than our competitors	3.67	1.18	0.75	0.69	0.81
		13. We compress time from product concept to marketing to respond quickly to the changes in customer needs	3.87	0.99	0.74	0.68	0.80
		14. We can quickly change our product mix in response to changing market opportunities	3.80	1.06	0.72	0.65	0.79
		15. We are fast at changing activities that do not lead to the desired effects	3.83	1.07	0.67	0.59	0.75

Source(s): Table by authors'

Table 5. Exploratory Factor Analysis solution (EFA) on the exogenous indicator variables

Variable	Broad knowledge skills	Specific technical knowledge skills
Technology management knowledge 2	0.668	
Business and marketing knowledge 3	0.662	
Relational knowledge 2	0.642	
Business and marketing knowledge 2	0.638	
Technical knowledge 4	0.632	
Technology management knowledge 1	0.626	
Technical knowledge 2	0.596	
Relational knowledge 4	0.595	
Business and marketing knowledge 1	0.584	
Technology management knowledge 3	0.574	
Technology management knowledge 4	0.568	
Relational knowledge 1	0.542	
Business and marketing knowledge 4	0.529	
Technical knowledge 3		0.850
Technical knowledge 1		0.605
Relational knowledge 3		0.533

Source(s): Table by authors'

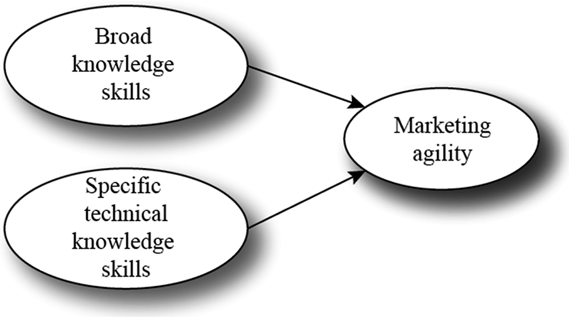


Figure 2. The modified structural model in the study

Source(s): Figure by authors'

loadings were significant to their relevant construct even though, in some cases, the outer loadings were marginally below the 0.70 threshold value. Therefore, there was no need to remove any indicator variables (Rosenbusch *et al.*, 2018).

The next step was the assessment of internal consistency reliability (Table 6). It is important to note that Cronbach's alpha is a conservative measure of reliability. In contrast, the composite reliability tends to overrate the internal consistency reliability (however, the target range for both measures is between 0.70 and 0.95). Thus, the actual reliability is between these criteria, where Cronbach's alpha value is the lower bound, and the composite

Table 6. Construct reliability and convergent reliability

Construct	Cronbach's alpha	Composite reliability	AVE
Broad knowledge skills	0.928	0.938	0.537
Marketing agility	0.936	0.955	0.527
Specific technical knowledge skills	0.805	0.885	0.719

Source(s): Table by authors'

reliability is the upper bound for internal consistency reliability (Hair *et al.*, 2022). Based on this, the internal consistency reliability is acceptable. Then, convergent validity was assessed with the average variance extracted (AVE) values. It was deemed satisfactory, as the threshold level 0.50 was exceeded for all constructs (see Table 6).

The next step in assessing the measurement model was the assessment of discriminant validity, which indicates the extent to which a construct differs from other constructs (Hair *et al.*, 2022). Recent literature suggests that the Heterotrait-Monotrait (HTMT) of the correlations, which signifies the ratio of the between-trait correlations to the within-trait correlations, is more accurate (Hair *et al.*, 2022) than the traditional Fornell and Larcker (1981) criterion. So, this was used to assess discriminant validity. Previous research has suggested that the threshold value of 0.90 should not be exceeded for the HTMT values (Henseler *et al.*, 2015). 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. For that reason, bootstrapping procedures were applied to test the significance (Hair *et al.*, 2022). If the bootstrap confidence interval includes the value of 1, it indicates a lack of discriminant validity. As seen from Table 7, none of the confidence intervals include the value of 1, thereby indicating discriminant validity.

The analysis above also has implications for the hypothesis development in this research. As a result, instead of having four 3-part hypotheses, there will be three 2-part hypotheses, which are as follows:

H1a. Broad knowledge skills have a positive and significant impact on the marketing agility of the firms at the limited deployment level of BDMA.

H1b. Specific knowledge skills have a positive and significant impact on the marketing agility of the firms at the limited deployment level of BDMA.

H2a. Broad knowledge skills positively and significantly impact the firms' marketing agility at the general deployment level of BDMA.

H2b. Specific knowledge skills positively and significantly impact the marketing agility of the firms at the general deployment level of BDMA.

H3a. Broad knowledge skills positively and significantly impact the marketing agility of the firms at the mature deployment level of BDMA.

H3b. Specific knowledge skills positively and significantly impact the marketing agility of the firms at the mature deployment level of BDMA.

Assessment of the structural model

The structural model assessment starts with evaluating collinearity, which indicates a correlation between the model's exogenous predictors (or constructs). Collinearity is usually assessed with the variance inflation factors (VIF). All VIF values in the structural model were

Relationship	HTMT value	Confidence interval 2.5%	Confidence interval 97.5%
Marketing agility ↔ Broad knowledge skills	0.909	0.857	0.954
Specific technical knowledge skills ↔ Broad knowledge skills	0.886	0.802	0.967
Specific technical knowledge skills ↔ Marketing agility	0.741	0.616	0.856

Source(s): Table by authors'

Table 7. Bootstrapping significance of the Heterotrait-Monotrait correlations

below the stringent threshold value of 3; thus, there were no collinearity issues (Hair *et al.*, 2011).

The next step was the assessment of the predictive validity of the structural model, which is typically assessed with the R^2, R^2 adjusted, and Stone and Geisser Q^2 values (Geisser, 1975; Stone, 1976) (see Table 8). 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-SEM model (Hair *et al.*, 2020). Based on this, marketing agility has substantial predictive validity and relevance.

Effect sizes and hypothesis testing

The final step in the structural model assessment was the estimation of the path coefficients, which, in this case, coincided with hypothesis testing. The results are presented in Table 9 and Figure 3. It is to be noted that the graphical illustration in Figure 3 represents only the complete data set, as the situation at the various levels of deployment was similar to the complete data set. Extant research has indicated that statistical significance is insufficient when reporting the results, and therefore, the effect sizes have been examined (Cohen, 1990;

Table 8. Predictive validity and relevance

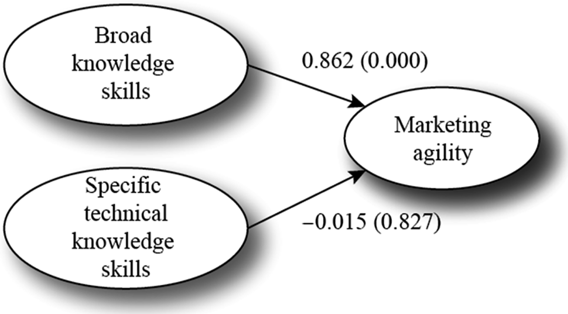
Construct	R^2	R^2 adjusted	Q^2
Marketing agility	0.723	0.721	0.711

Source(s): Table by authors'

Table 9. The significance of the path coefficients and effect sizes in the model

#	Exogenous construct	Path coefficient	*p*-value	Hypotheses support	Effect size (f^2)	Effect
Complete data set	Broad knowledge skills → Marketing agility	0.862	0.000	–	1.105	Large
	Specific technical knowledge skills → Marketing agility	−0.015	0.827	–	0.000	–
Deployment level 5	Broad knowledge skills → Marketing agility	0.784	0.000	Yes	0.707	Large
	Specific technical knowledge skills → Marketing agility	−0.066	0.668	No	0.005	–
Deployment level 6	Broad knowledge skills → Marketing agility	0.827	0.000	Yes	1.412	Large
	Specific technical knowledge skills → Marketing Agility	0.103	0.148	No	0.022	Small
Deployment level 7	Broad knowledge skills → Marketing agility	0.893	0.000	Yes	1.380	Large
	Specific technical knowledge skills → Marketing agility	−0.015	0.860	No	0.000	–

Source(s): Table by authors'



Source(s): Figure by authors'

Figure 3. The path coefficients and their significance in the model

Klein, 2005). The effect size may be the most critical finding in the statistical analysis as, with a sufficiently large sample size, statistical testing can find significant differences that are meaningless in practice. For that reason, the reporting of the *p*-values is insufficient (Sullivan and Feinn, 2012). The effect size is not influenced by sample size; therefore, it is comparable across different research studies (Hair *et al.*, 2010). Literature has denoted that the values of 0.02, 0.15, and 0.35 indicate that the exogenous constructs have small, medium, or large (direct) effect sizes, respectively (Hair *et al.*, 2022).

Discussion

This research aimed to examine the dimensionality of the knowledge and agility constructs, the relationship between the knowledge and agility constructs, and the impact of the degree of BDMA deployment on this relationship. We will begin by discussing the dimensionality of our two primary constructs: knowledge and marketing agility.

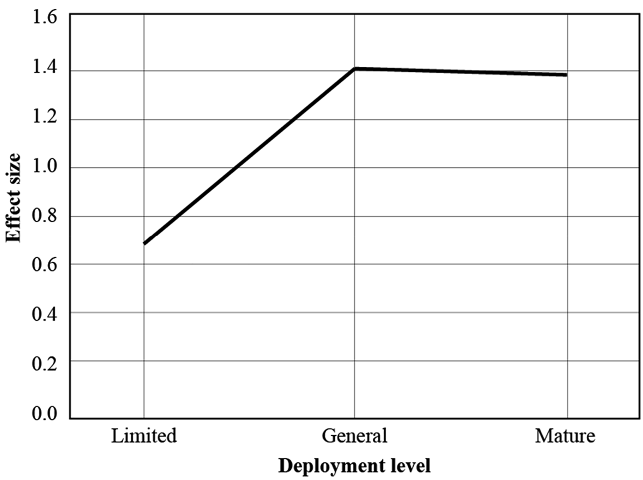
Previous research discovered that the knowledge construct was multidimensional, consisting of technical, technology management, business/marketing and relational dimensions (Akter *et al.*, 2016; Garmaki *et al.*, 2016) when the sample consisted of business analysts, big data analysts, and IT professionals. Accordingly, one of the research questions was to examine whether marketing professionals (the service users) perceived the knowledge construct in the same way that the business analysts, BD analysts, and IT professionals (the service providers) did. The results of this research illustrate that marketing professionals viewed the knowledge construct to consist of only two factors: broad knowledge and specific technical knowledge. Therefore, the marketing professionals (i.e. the service users) perceived the required knowledge as much more straightforward than the service providers. This may be explained by the fact that the service users are less familiar with the precise and detailed nature of the knowledge than the more experienced and knowledgeable service providers. Accordingly, it would make sense for less experienced BDMA individuals to perceive the knowledge more straightforwardly. Based upon this, knowledge structures (and other similar constructs) may need to be revisited every time we study a population with different levels of expertise and interest in a subject.

Previous research revealed the marketing agility construct to be a multidimensional construct consisting of proactiveness, responsiveness, flexibility, and speed dimensions (Haverila *et al.*, 2024; Zhou *et al.*, 2019). However, the current research found that marketing professionals perceived marketing agility as unidimensional. Again, the relatively less knowledgeable marketing professionals may perceive the factors of proactiveness, responsiveness, flexibility, and speed as similar and interchangeable. Naturally, an individual with more IT and analytics experience would be able to discern and understand these subtle differences among the factors. However, it may be more complex for an individual less familiar with the nuances within the IT and BDMA domains. Once again, this supports the notion that differing levels of expertise may lead to different results of these complex constructs from a statistical and practical standpoint.

Now that we have discussed measurement implications, we will discuss the structural model. The quality of the resulting measurement and structural models created to understand the relationships between these constructs was deemed good (see Figure 3), with acceptable indicator reliability, composite reliability, convergent and discriminant validity, and substantial explanatory/predictive power.

When looking at the relationships between the two knowledge constructs and marketing agility, the results found the first construct (i.e. broad technology, technology management, business/marketing and relational skills) to be highly significant in the whole data set as well as at the three deployment levels (limited, general, and mature). However, the relationships between the second knowledge construct (i.e. specific data, network management and educational collaboration skills) and marketing agility were found to be insignificant. Also, the effect sizes at the three deployment levels were large for the broad knowledge skills. So, they didn’t just have a statistical effect on marketing agility but instead made a sizable difference in the perceived adaptability of the organization.

The effect sizes increased remarkably from the limited to general deployment level and remained very high at the mature level of BDMA deployment (see Table 9), meaning that more experienced BDMA professionals found this impact stronger than less experienced BDMA users. This is also consistent with the increasing mean values of the various constructs at different deployment levels in Table 4, where the advancement of the mean values is particularly striking with the agility constructs. Looking at the rise of the effect sizes and the mean values, critical progression happens from the limited to the general deployment stage, after which the effect sizes and mean values plateau (see Figure 4). This finding demonstrates the significance of adequately investing in the deployment of BDMA. If a company is to benefit from BDMA truly, it must go beyond the bare minimum (i.e. a limited deployment) and go “all-in” with its deployment.



Source(s): Figure by authors’

Figure 4.
The effect sizes at the various deployment levels

Accordingly, BDMA should be seen as something other than a technology or process used by a few individuals in specific departments in certain situations. Instead, it should be ingrained into a company's entire culture in all relevant decisions and strategies. Broad knowledge impacts the effectiveness of a BDMA program, and marketing professionals will become more convinced of this as their use of the system increases. This finding also highlights the need to study individuals with various backgrounds/levels of expertise separately to understand their unique experiences and perspectives better. They all experience the same organizational strategies differently.

Agility theory highlights the importance of proactiveness, responsiveness, flexibility, and speed dimensions (Haverila *et al.*, 2024; Zhou *et al.*, 2019). This research verified the importance of all these dimensions. However, the current study found that agility was perceived as unidimensional instead of 4-dimensional. Thus, the results contradict the findings of Zhou *et al.* (2019).

Dynamic capabilities theory states that organizations need to be proactive in making change – that there are strengths that lead to success in the current marketplace. Still, some strengths help the organization adapt to market changes (Teece *et al.*, 1997). BDMA deployment, when done well, is a core source of the second type of strength that will enable an organization to see changes in the marketplace and determine what changes in their organization will be required. The strong relationship between broad knowledge and agility shows that effective deployment of a BDMA system can and will lead to a firm's ability to be more agile in the marketplace, as dynamic capabilities theory requires.

The results of this research are also congruent with organizational learning theory because the relationship between the new broad knowledge construct was significant in all deployment stages, and there were also increasing effect sizes, especially between the limited and general BDMA deployment levels. This is evident as the performance measures (both knowledge and agility) made significant progress with the advancement of deployment, which can be explained by employees acquiring (explicit and implicit) knowledge and experience (Huber, 1991). As mentioned, performance should improve with the evolution of the learning curve. Based on this, one could expect performance measures to improve (whether qualitative or quantitative) with the advancement of deployment in the BD context. The essence of quality function deployment theory (which is similar to organizational learning theory) is to create a quality BDMA system so that internal customers (i.e. the users of BDMA) are satisfied (Arthur and Huntley, 2005). Based on the findings of this research, the quality of the BDMA appears to reach its peak at the general level of deployment and stays there during the mature level of deployment. The current study confirms that BDMA deployment follows the general pattern expected based on organizational learning theory, demonstrating its applicability in yet another context.

Implications

From the theoretical point of view, investigating the dimensionality of the constructs in any research is critical. Invariance at the measurement and construct levels is essential, as the lack of invariance may cause problems when analyzing samples. Therefore, making conclusions from the combined data set may be challenging. This research also confirms the critical role of embedded broad knowledge among the BDMA personnel when aiming to enhance marketing agility.

The researchers should carefully investigate the reasons for the lack of invariance in the sample population and whether the reason might be in construct, method, or item bias (Davidov *et al.*, 2014). If the problem lies at the construct level, like in this research, the conceptualization of the constructs by the populace should be examined. Construct bias is the primary form of bias and signifies that the theoretical concept has a different meaning for some of the respondents in the sample population. Dissimilar views may be discovered in the subpopulations when comparing the measurement scores, making the analysis challenging. Thus, the inability to compare theoretical constructs risks comparative research in social sciences (Davidov *et al.*, 2014; Meredith and Teresi, 2006). It is essential to carefully re-examine the measurement construct whenever a different population is being studied to ensure proper measurement and comparability across findings.

From a practical perspective, the findings suggest that BDMA managers need to recognize these domain-specific differences. This indicates that marketing agility is best achieved through building broad technical, technology management, business/marketing and relational knowledge skills among the personnel in the BDMA context rather than having specialized business/marketing, technical, technology management or relational skills. This makes sense because marketing agility is all about being prompt and responsive to the changes in the business environment, and that can arguably be achieved through broad knowledge skills; it may not be necessary to have more specific knowledge skills because they may be perceived to improve marketing agility in a relatively marginal sense. This finding is consistent with the McKinsey company's claim for rapidity in releasing agile, empowered teams with multidisciplinary skills using analytics to make swift decisions (McKinsey, 2023).

Finally, marketing practitioners should recognize the critical role of knowledge accumulation throughout the deployment of BDMA in their organizations. This is particularly critical when proceeding from the limited deployment stage to the mature deployment stage, as the accumulation of knowledge may cause a significant increase in the effect size toward marketing agility between these stages. Accordingly, managers must invest the right resources into deploying BDMA across the firm. As mentioned earlier, for BDMA to be successfully implemented in a firm, it must be a part of the ethos and culture of a firm and used in all relevant decisions and strategies. Furthermore, organizations should not be discouraged if they don't get all they want out of the system right away – the usefulness of a BDMA increases drastically as the level of deployment increases from limited to general. However, it is essential to note that the effect size plateaus between the general and mature deployment stages, which shows that the impact seems to level off at this point. This illustrates how any technology or analytical technique, no matter how useful, will eventually reach its limits concerning its value in a firm. Consequently, managers must realize this and balance BDMA deployment and investment appropriately, remembering the law of diminishing returns for all investments.

Limitations and future research

This study focused on two critical constructs in the BDMA domain, i.e. knowledge and marketing agility. Differences were discovered between the research sample (the marketing professionals) and the samples (e.g. IT management) in previous research. Differences of similar significance may exist across other relevant construct domains and samples, such as industry type. The results indicate that examining various constructs' dimensionality is essential in social science research. However, the "narrowness" in the sample selection may considerably bias the research results.

Even though we discovered significant differences between the various types of respondents, this research did not examine why these differences might exist. So, exploring why these differences occur may be an intriguing research venue. One possible reason for the perceptual discrepancies is that the respondents from different domains (marketing vs IT) conceptualize the indicator variables and constructs differently. The wording of the questions may produce different responses from respondents from other professional disciplines. Related to this, previous research has emphasized that words, phrases, items, and response options need to be straightforward, unambiguous, and similar for all respondents who belong to the target sample (Patrick *et al.*, 2011). The differences caused by these issues may lead to different response patterns, a phenomenon well-known in cross-cultural research (Khan *et al.*, 2009).

The paper contributes to marketing analytics research and identifies the critical antecedent of marketing agility, i.e. knowledge in the context of BDMA. The sample consisted of marketing professionals working in companies with at least limited experience in the deployment of BDMA. Therefore, aiming to generalize the findings in other related contexts must be done carefully. A crucial undertaking for researchers should be to establish if theories and models recognized in one domain (e.g. information technology) are appropriate in another domain (e.g. marketing). In this research, the conceptualization of the knowledge and marketing agility constructs completely differed between the respondents originating from the marketing and IT domains. Based on this, future research should examine the existence of factorial invariance and measurement equivalence between groups with multi-group confirmatory factor analysis.

Finally, as previous research has identified the dependence of dynamic capabilities on knowledge of varying levels of market dynamism (Eisenhardt and Martin, 2000), future research could explore the impact of market dynamism in the framework of this research. For example, one could examine the dimensionality of the knowledge and marketing agility constructs under different market dynamism levels and the strength of the relationship between the knowledge constructs and marketing agility.

Conclusions

This research examined the relationship between the critical knowledge construct and marketing agility with a sample ($N = 236$) of marketing professionals working in firms with at least limited experience in BDMA deployment. As the sample frame differed from those used in previous research, the dimensionality of the knowledge and marketing agility constructs was examined first, and differences in conceptualization were discovered. This study revealed two primary knowledge constructs: broad knowledge and specific technical skills. Of these, only the broad knowledge skill construct was significantly and positively related to the marketing agility construct. The level of deployment (limited, general, and mature) influenced the relationships between knowledge level and agility. However, marketing professionals at various stages of BDMA deployment recognized the crucial role of broad knowledge skills in utilizing data effectively to increase agility – but more experience leads to an even greater appreciation of the importance of these skills. The overall quality of the structural and measurement models was good.

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