Industrial Marketing Management 92 (2021) 178–189

Contents lists available at ScienceDirect

Industrial Marketing Management

journal homepage: www.elsevier.com/locate/indmarman

Research paper

An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance

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ARTICLE INFO

Keywords:
Artificial intelligence
Big data
Knowledge management
B2B marketing
Firm performance

ABSTRACT

This study examines the effect of big data powered artificial intelligence on customer knowledge creation, user knowledge creation and external market knowledge creation to better understand its impact on B2B marketing rational decision making to influence firm performance. The theoretical model is grounded in Knowledge Management Theory (KMT) and the primary data was collected from B2B companies functioning in the South African mining industry. Findings point out that big data powered artificial intelligence and the path customer knowledge creation is significant. Secondly, big data powered artificial intelligence and the path user knowledge creation is significant. Thirdly, big data powered artificial intelligence and the path external market knowledge creation is significant. It was observed that customer knowledge creation, user knowledge creation and external market knowledge creation have significant effect on the B2B marketing-rational decision making. Finally, the path B2B marketing rational decision making has a significant effect on firm performance.

1. Introduction

Business-to-business (B2B) marketing has offered new prospects and challenges in this digital age (Bhandari et al., 2017; Rust, 2020). Digital B2B marketing models have been found to surpass traditional models (Bhandari et al., 2017). Furthermore, Davenport, Guha, Grewal, and Bressgott (2019) indicated that artificial intelligence is on course to disrupt marketing management. In a complex business environment, B2B marketers need smart solutions to automate the process of structuring, standardising, aligning and customising data (Fensel et al., 2001; Jabbar, Akhtar, & Dani, 2019). Leveraging big data to activate artificial intelligence (AI) technologies provides marketers with a competitive edge and is reflected in marketing strategies and customer behaviours that generate further positive outcomes (Jabbar et al., 2019). Big data coming from social media and search engines can offer important insights for B2B marketers and help build programmes for online advertisements and customer assistance in a pioneering manner (Jabbar et al., 2019). Lee, Dabirian, McCarthy, and Kietzmann (2020) provided a roadmap for performing AI-enabled content analysis in the field of marketing. The role of the sales force is changing, and reliance on technology and analytics in order to achieve success is increasing (Sleep, Dixon, DeCarlo, & Lam, 2020). To avoid problems when decoding big data sets, Chen et al. (2020) recently provided an overview approach using cognitive computing techniques to evaluate unstructured data sets generated from users. Advances in technology have created a deep impact on marketing. It may be difficult to fully comprehend, but big data has enabled AI to such an extent that it has disrupted marketing management and made the traditional "4P" model increasingly outdated (Rust, 2020). The more available big data sets are, the stronger AI applications will be, since machines will be able to reason and act more effectively. AI technologies can help in the selection of international marketing strategies and effective marketing programmes (Katsikeas, Leonidou, & Zeriti, 2019). The literature indicates that although B2B companies use digital marketing tools, most of them fail to exploit them fully. There is a dearth of academic literature available in this area (Pandey, Nayal, & Rathore, 2020).

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https://doi.org/10.1016/j.indmarman.2020.12.001
Received 27 June 2020; Received in revised form 6 December 2020; Accepted 7 December 2020
Available online 22 December 2020

Paschen, Kietzmann, and Kietzmann (2019) explained the role of AI in contributing to the knowledge creation in B2B marketing. This study highlighted some key research areas for the future such as: (a) the role of AI in capturing customer knowledge; (b) understanding the movement of user knowledge in B2B marketing; (c) how AI can be leveraged to enhance the market understanding abilities using external market knowledge.

Technology acts as an enabler in the domain of knowledge management apart from organisational structure and culture (Syed-Ikhsan & Rowland, 2004). Big data powered AI technology (BDAI) acts as a key technological enabler in this digital age (Dubey et al., 2019), particularly for knowledge creation and decision making (Duan, Edwards, & Dwivedi, 2019). Importantly, there is limited research available for such interplay. Hence,

RQ1. Can big data powered AI enhance knowledge creation in B2B marketing?

Customer knowledge, user knowledge and external market knowledge are important parts of the knowledge management process and are responsible for knowledge creation in B2B marketing (Abubakar, Elrehail, Alatailat, & Elçi, 2019).

Big data can be useful for extracting important information such as web browsing behaviour, demographic features and purchasing patterns from structured and unstructured data inputs and provide useful customer knowledge for rational decision making. User knowledge is also important for developing new products, innovating and improving processes. Psychographic characteristics can be immensely helpful for B2B marketers in developing innovative products (Paschen et al., 2019). External market knowledge is important to stay ahead of competitors. Competitive intelligence can be created using AI by analysing unstructured data such as news and social media content that can help B2B marketers make better decisions, improve analytic and decision making capacity and enhance creativity (Paschen et al., 2019). Knowledge management and decision making styles are critical for the success of organisations in this digital age (Abubakar et al., 2019). The rational decision making style depends on quality information to make the right choices. This methodological approach involves scrutinising available alternatives when making decisions. It also enhances organisation performance (Smolka, Verheul, Burmeister-Lamp, & Heugens, 2018). The literature indicates a positive association between knowledge management processes and organisational performance (Abubakar et al., 2019; Wu, 1998). Knowledge management systems work as superior decision support systems for organisations and eliminate operational bottlenecks (Powell & Swart, 2010).

Again, very few studies are available that have examined the synergy and convergence of these interesting relationships in the field of B2B marketing. It would therefore be worth investigating and answering the following research question:

RQ2. Can knowledge creation improve B2B rational marketing decision making and further enhance firm performance?

Lilien (2016) highlighted the existence of a B2B knowledge gap and suggested stronger academic research output to fill the gap and enable knowledge creation. This study offers relevant and rigorous research output that is practice oriented and extends the knowledge base. Our theoretical model is grounded in Knowledge Management Theory (KMT) and the model has been statistically validated using B2B data from South Africa. The data was collected from mining industry. Technological change and changing consumer behaviour have emerged as a major concern for the mining industry. The South Africa mining industry is in transition from a conventional mining environment to a mechanised shallower, technologically advanced industry. To stay competitive mining companies are adopting digitalisation as a basic part of their new business model encircling all functions: supply chain, marketing and sales and in particular interactions with current and potential customers. This is due to changing consumer behaviour as they link the product with their societal and environmental effect and have the platforms to gain publicity through social media. Therefore, the responsibility is at the present on mining companies to leverage digital technologies to reach out and exhibit that they have fulfilled their commitments towards environment and society (SA Mine report, 2020).

In managing the B2B marketing of a firm, decisions often have to be made in an environment having some underlying uncertainty. Some examples include segmentation and targeting customers, understanding customer requirements, obtaining data/specifications, offering samples for trial, sales channel management, budgeting, investment in marketing activities, and customer relationship management. In a volatile business environment, decision making further becomes difficult. This study discusses decision making in B2B marketing management context using digital technologies, with a focus on extension of theory and making theoretical contribution based on this empirical study.

Alvesson and Sandberg (2011) proposed a scientific method of deriving research questions by adopting the problematization approach. This method is good for finding and contesting assumptions related to the existing theories and further derive the research questions.

However, the commonly used approach taken by past researchers is the gap-spotting method. This gap-spotting method can reinforce or abstemiously revise already established theories (Sandberg & Alvesson, 2011). In the current study the research team favoured gap-spotting method to derive the research questions. In specific, the research team used “application spotting” approach that can extend and complement prevailing theory.

Hence, this study extends the knowledge base in the industrial marketing management area from three perspectives: First, this study considers a very important industry from an emerging economy. Secondly, this study considers the knowledge management enabler from technology (big data powered artificial intelligence) point of view, which is a very important dimension of Industry 4.0. Thirdly, this study tested Knowledge Management Theory under industrial marketing management context and demonstrated key links between knowledge management enabler (big data powered artificial intelligence); knowledge management process (customer knowledge creation, user knowledge creation, external market knowledge creation); decision making style (B2B marketing rational decision making) and organisation output (firm performance).

Future research needs to examine the organisational and environmental factors that could influence the extent of knowledge management process and further impact on the decision making style.

The next section presents the scientific debate surrounding model development followed by the creation of research hypotheses. The third section explains the research method that dictated the research flow. Analysis are presented in section four, and the final section provides a framework for discussion by comparing findings with previous studies. The conclusion sets forth the theoretical and practical implications. All practical research work faces some resource constraints, and our study was also confronted with a few of them. The limitations of this work and some food for thought intended for future researchers are showcased at the end.

2. Theoretical foundation and hypothesis development

2.1. Big data powered artificial intelligence

AI is the science of creating smart machines using algorithms to help computers solve problems that can be solved by human beings. As far as the history of AI is concerned, AI was incubated between 1943 and 1955 and finally took birth in the Dartmouth workshop in 1956. Unfortunately, there was an AI winter from the late 1960s to the late 1970s. This occurred for various reasons, one of them being a derogatory report submitted by Prof. Sir James Lighthill on the state of AI in the United Kingdom. AI research subsequently attracted criticism from the U.S. Congress and funding gradually decreased in the field of neural-net studies. However, from the 1980 onwards, the commercialisation of expert systems in private organisations was noticed (Haenlein & Kaplan, 2019). The application of intelligent agents such as robots began in 1995 and 2001 witnessed the birth of big data. Big data has empowered AI significantly, enabling AI to power search engines, e-buying and digital assistance (Batistič & van der Laken, 2019). In 2005, Prof. Geoffrey Hinton discovered a unique process to efficiently train neural networks.

AI is a sub-field of computer science. The capabilities of AI include sensing, reasoning and acting, and some recent work has focused on developing human reasoning in machines to activate them thinking and working like humans.

AI has made significant contribution in the production and distribution of goods. Robots controlled by computer systems is playing an important role in boosting output.AI powered automation has resulted into higher efficiency and output levels at a much lesser costs.AI has brought collaborative robots, self-adapting assembly lines, system for maintenance. For instance, General electric is using system named Predix to monitor goods in the field. AI is gaining popularity in banking, finance and insurance industries. Algorithms offer innovative and tailor-made services (eg., algo-trading, robo-advisors) (Krüger, Lien, & Verl, 2009).

Machine learning (ML) primarily use algorithms and data to make decisions. ML has huge importance in B2B marketing. For instance, it can generate rich insights from data related to customer buying behaviour and help in making good decisions (Cortez & Johnston, 2017; Wright et al., 2019; Liu, 2020).

Supervised learning, unsupervised learning and reinforcement learning are the main ML techniques (Lison, 2015). Supervised learning uses labelled data. Labelled data refers to data in which a label has been correctly assigned to a known feature (or features) of the data. Unsupervised learning means just that! Scientists do not supervise the model; they do not provide examples of objects with attributes and labels. In unsupervised learning, the model learns on its own. Reinforcement learning draws from behaviourism and is a psychological perspective of human behaviour (Lison, 2015).

Deep learning is gaining importance but we need to remember that it is different from ML. Nueral networks are utilised in deep learning to generate solutions (Batistič & van der Laken, 2019).

Mining is an important economic sector that influences the economic development of a country. The adoption of AI, ML and autonomous technologies (AT) was started in the mining industry about a decade ago (Hyder, Siau, & Nah, 2019). AI and AT have benefitted prospecting and exploration. AI and ML can be useful in developing autonomous drills. Not only that-AI, ML and AT can prevent mining workers from coming in contact with hazardous environment by sending signals and warnings. Autonomous mining haulage trucks, loaders and excavators are gaining popularity as they can operate for 24 × 7 continuously (Hyder et al., 2019).

Thus, AI research has also been extended to the field of marketing science. Evaluating big data sets that come from various sources and demographics helps marketers to understand which parameters can improve marketing performance. Big data analysis reveals themes and patterns that AI can use to further enhance the efficacy of marketing strategies (Paschen et al., 2019).

Research aiming to develop theory is a popular subject among social science researchers. Theory is a proclamation of relationships among concepts within a set of boundary suppositions and restraints (Bacharach, 1989). Organisation theories can elucidate behaviours, designs and structures (Bacharach, 1989). De Camargo Fiorini, Seles, Jabbour, Mariano, and de Sousa Jabbour (2018) addressed various organisational theories related to large data research. They also provided a research schema to connect organisational theories to large data based empirical research. De Camargo Fiorini et al. (2018) specifically indicate that Knowledge Management Theory (KMT) can be helpful to investigate various aspects of large data adoption. The next section discusses the KMT to explain the technological application, processes and help B2B marketers to enhance firm performance.

2.2. Knowledge management theory (KMT)

Knowledge management is a popular strategy to enhance the competitive position of an organisation (DeTienne & Jackson, 2001; Dwivedi, Venkitachalam, Sharif, Al-Karaghouli, & Weerakkody, 2011). Organisational learning can aid in building new knowledge or providing insights that can change behaviour (McElroy, 2000). Knowledge can be either explicit or tacit. Explicit knowledge is knowledge that has already been documented in some form (files, databases, manuals, etc.), whereas tacit knowledge is present only among employees and considered an important knowledge resource in any organisation. Through accessing, sharing and adopting both explicit and tacit knowledge, an organisation can dramatically enhance performance (DeTienne & Jackson, 2001). In the 21st century, knowledge has proven to be an important part of production. It is essential for any organisation to learn and adapt in a volatile environment to enhance profit margins. Therefore, the knowledge-based approach is an important pillar for any organisation (Tzortzaki & Mihiotis, 2014).

KMT primarily focuses on structural, cultural and technological enablers to manage knowledge and knowledge processes (Abubakar et al., 2019). The theoretical foundation of knowledge management was laid by Hazlett, Mcadam, and Gallagher (2005) and Baskerville and Dulipovici (2006). Although this theory is more popular in information systems research, KMT can be used for new concepts that provide logical reasoning for managing knowledge and can help define knowledge management processes to project the outcome of a process (Baskerville & Dulipovici, 2006). KMT has been extended to the domain of relationship marketing (Rowley, 2004). Knowledge management and relationships may be different concepts, but they both involve communication, as has been shown in the literature on both. Customer data is useful in relationship management, and knowledge management thus creates an interesting interface for further research (Rowley, 2004).

B2B marketing has recently gained significant attention due to the economic power of its transactions (Cortez & Johnston, 2017). Theoretical advancements have occurred in the last decade and future research needs to focus on innovation, customer relationships, data analytics exploiting technology to increase income and the industrial environment (Cortez & Johnston, 2017).

This study aims to address the calls of previous researchers and to develop the theoretical model based on the preceding discussions (Fig. 1). The model for this study considers big data, AI technology and organisation performance aspects in the context of the mining industry.

Knowledge management can be used to deal with the diffusion and development of knowledge and to analyse the knowledge features of a relationship in order to handle it more efficiently (Powell & Swart, 2010). Knowledge is an amalgamation of contextual information, the experience of experts and value that can result in innovation (Abubakar et al., 2019). Knowledge management can improve creativity and enhance organisational performance. Knowledge management enablers are driving factors that can enhance knowledge management-related tasks. These driving factors are organisational structure, organisational culture and technology. The role of information technology in eradicating communication-related barriers is noteworthy. Information technology aims to improve mutual learning, knowledge and proper communication (Abubakar et al., 2019).

The knowledge management process consists of steps such as acquiring, designing, managing and disseminating knowledge to improve organisational performance.

Knowledge assets including inputs, outputs and brokers are important parts of the knowledge creation process. The knowledge management process can influence the decision making style. A decision making style can be intuitive or rational. However, the rational decision making style is a methodological process and requires intensive information. The final output can be individual performance/organisation

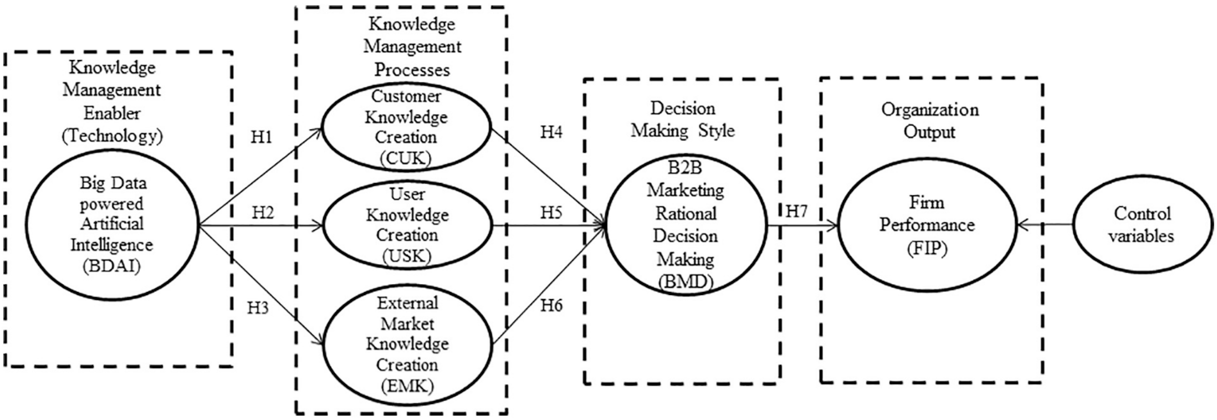

Fig. 1. Theoretical model.

performance. Knowledge management systems can improve organisational efficiency and lower operational barriers. They help make better decisions and improve revenue (Abubakar et al., 2019). B2B marketers also need to focus on data security aspects to reduce any kind of breach (Trim & Lee, 2019).

The main pillars of our theoretical model are knowledge management enablers, knowledge management processes, decision making style and organisational output (Paschen et al., 2019). The knowledge management enabler considered in our study is a technology (BDAI) that helps streamline the knowledge management process by creating customer knowledge, user knowledge and external market knowledge. This knowledge creation also leads to a rational B2B decision-making style which enhances firm performance (Paschen et al., 2019). BDAI construct considered in this study is mainly related to the management of unstructured and structured data sets and further use them in automating certain steps of B2B marketing and sales. CUK construct is related to the use of AI to utilise structured and unstructured data of different nature and perform analysis related to attitude and behaviour of customers. Since user knowledge is important for developing new products and enhancing creativity. Therefore, USK in B2B context is considered in this theoretical model. AI-enabled knowledge about users may indicate how users modify some products themselves and such information can be helpful for new product developments (Paschen et al., 2019).

EMK is considered in the theoretical model as external market knowledge gives competitive edge to B2B marketers and this study focuses on BDAI that can be used to gather intelligence about external market forces and stakeholders (Paschen et al., 2019).

Another very important construct used here is BMD; as B2B marketing rational decision making is essential in this volatile business environment. BDAI technology enables in undertaking complex work and in making better informed decisions (Duan et al., 2019).

The endogenous construct i.e. firm performance measures the financial and marketing performance of the firm; for instance, ability to retain customers much better than competitors, improvement in ROI and market share (Wamba et al., 2017). The research team considered the effect of control variables such as size of firm and firm age. Literature indicates that larger the size of the firm; the greater is the capability to acquire and access resources. Similarly, the more is the age of the firm, the greater is the maturity level and high chances of adopting advanced technologies. Therefore, it is important that both these variables be controlled during the study to get accurate results.

2.3. Hypothesis development

The seven research hypotheses were discussed as under.

2.3.1. Big data powered artificial intelligence and customer knowledge creation

In this digital age, organisations have access to big data sets that are structured/unstructured for analysis (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2019). However, marketers face two major challenges when using data that are available from social media. First, the unstructured nature of the data; and second, the fact that the high volume of data sets makes the standard analysis process impracticable (Liu, Singh, & Srinivasan, 2016). Balducci and Marinova (2018) contributed to the literature by performing research on the usefulness of unstructured data in marketing. The analysis of such data sets requires advanced analytical methods and computational techniques (Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019). Data visualization methods help B2B marketers decode complex data and gain insights for decision making (Duan et al., 2019). AI bots have gained popularity recently, and they can automate selling activities, supplementing the capabilities of existing sales force (Leung, Luk, Choy, Lam, & Lee, 2019; Paschen et al., 2019).

Big data analytics (BDA) can exploit structured and unstructured data and extract key information such as web browsing frequency, types of industrial product searches, purchase history and buyer attributes that can help develop knowledge about customers (Chintagunta, Hanssens, & Hauser, 2016). B2B marketers can also use ML and predictive analytics tools to develop the profile of current and future customers and devise a relationship strategy accordingly (Hofacker, Golgeci, Pillai, & Gligor, 2020; Paschen et al., 2019). Every stage of the B2B sales process can be augmented with BDAI. B2B marketers can use the predictive modelling approach to identify high quality business leads without utilising many human resources. At the final stage of the sales process, B2B marketers can use AI presentation bots to prepare exceptional presentations. Emotion AI can be useful in negotiations when making business deals and prevail over any doubts that may arise in the customer's mind. AI can also help reduce competition and enhance an organisation's own value offerings. AI-based chat bots can be beneficial in doing order follow-ups with industrial customers and automating order processing activities (Paschen et al., 2019). B2B marketing efficiency can therefore increase three-fold with the application of BDAI technology (Jabbar et al., 2019; Liu, 2020). Davenport et al. (2019) has indicated that advanced technologies like AI can change the future of marketing. This is possible by exploiting BDAI technology through the generation of knowledge from customers and further developing appropriate B2B marketing strategies (Bonnin & Rodriguez, 2019).

Therefore, we hypothesize:

H1. Big data powered artificial intelligence has a positive relationship with customer knowledge creation.

2.3.2. Big data powered artificial intelligence and user knowledge creation

The digital revolution has increased computational abilities and big data seems to have made AI more powerful in recent times (Duan et al., 2019). The literature indicates that BDAI can help create user knowledge for better decision making (Paschen et al., 2019). Social media marketing and advertising is gaining popularity (Dwivedi, Kapoor, & Chen, 2015). Content from social media platforms can be used for big data analysis and to gain further insights related to users' product buying needs, likes and attitudes towards industrial products. AI technology can identify buyer emotions and attitudes from text-based data. Psychographic features can be extremely useful for developing new products. Furthermore, BDAI enabled knowledge about users may reveal important information concerning user modifications of products and services (Huang and Rust, 2020) that can be valuable for product development (Paschen et al., 2019). Therefore, we hypothesize:

H2. Big data powered artificial intelligence has a positive relationship with user knowledge creation.

2.3.3. Big data powered artificial intelligence and external market knowledge creation

BDAI has proven to be highly beneficial in this digital age (Duan et al., 2019). AI models can be helpful to collect market intelligence data such as competitor activities, competitor product launches, changes in legislation and entry of new companies in the market (Paschen et al., 2019). AI helps with market knowledge creation by decoding online web-based content with the aid of big data analytics. Natural language processing (NLP) and ML tools can be helpful for assessing the quality of market news and distinguishing between fake news and content. This adds great value in B2B marketing programs. BDAI can create a competitive advantage by decoding important information from competitors' documents such as news or social media content (Paschen et al., 2019).

Therefore, we hypothesize:

H3. Big data powered artificial intelligence has a positive relationship with external market knowledge.

2.3.4. Customer knowledge creation and B2B marketing rational decision making

Customer knowledge creation is important to gain a competitive advantage and to stay ahead of competitors. Customer knowledge can help B2B marketers make rational decisions (Paschen et al., 2019). Rational decision making is a methodological approach that involves scrutinising alternatives and arriving at the optimal solution. AI can help B2B marketers make better decisions and increase creativity (Duan et al., 2019). When based on KMT, knowledge creation has been shown to be a vibrant, multifaceted and intricate process (Abubakar et al., 2019). Customer knowledge is an asset that can help in knowledge creation by converting tacit knowledge into explicit knowledge. Customer knowledge is relevant and can be relied on to perform big data analyses and used to make important choices. Since rational decision making is a cognizant and thoughtful process free from intuition, the quality of decision making is much higher. Rational decisions made based on customer knowledge can help make B2B marketing more effective (Paschen et al., 2019). Therefore, we hypothesize:

H4. Customer knowledge creation has a positive relationship with B2B marketing rational decision making.

2.3.5. User knowledge creation and B2B marketing rational decision making

User knowledge creation can be gained using BDAI technology enablement as discussed in the previous sections. User knowledge involves psychographic characteristics and user experiences, likes, dislikes, attitudes and behaviours towards a company's product and service offerings (Paschen et al., 2019). These data can be useful in making rational B2B decisions related to new product development and service offerings. B2B marketers can acquire, manage and process this rich information and create knowledge to further improve B2B marketing and sales processes. User knowledge creation brings an added advantage to B2B marketers when making rational choices by checking alternate options and probable consequences (Abubakar et al., 2019). Therefore, we hypothesize:

H5. User knowledge creation has a positive relationship with B2B marketing rational decision making.

2.3.6. External market knowledge creation and B2B marketing rational decision making

External market knowledge can keep B2B marketers informed about the latest happenings in the market. It allows B2B marketers to become cautious about competitors' activities and remain alert with regard to influences on their own brands. Fake news is often released by competitors to defame other brands, and these threats can be effectively managed by keeping abreast of the latest updates by leveraging BDAI technology (Paschen et al., 2019). Rational decision making involves the decisive assessment of facts in a planned process that requires time and hard work. External market knowledge creation can be captured, stored, processed and organised using BDAI technology for problem solving and decision making (Duan et al., 2019). Therefore, we hypothesize:

H6. External market knowledge creation has a positive relationship with B2B marketing rational decision making.

2.3.7. B2B marketing rational decision making and firm performance

Prior and Keränen (2019) suggested future research directions when they stated that attention must be given to decoding information for better solutions and that B2B marketing must be understood from an information requirement perspective. Rational decision making compels B2B decision makers to consider multiple situations and the probability of every selection before arriving at a given decision. Rational decision making criteria are established to explore a full set of choices. Therefore, it is important for relevant and reliable information to be available in order to make rational decisions. Rational decision making is free from assumptions and biases and thus leads to quality decisions and improved organisational performance (Smolka et al., 2018). Organisational performance involves the overall health of the organisation. Performance can be measured by comparing targets with actual performance. Knowledge management can help enhance organisation processes and eliminate other barriers by fostering rational decisions (Abubakar et al., 2019; Johnston & Chandler, 2012). B2B rational decisions can help retain customers and improve profit margins. B2B marketers can also quickly launch new products and penetrate new markets (Singh et al., 2000). Market share can improve significantly with the aid of rational decision making (Yu, Yu, Itoga, & Lin, 2008; Wamba et al., 2017; Wilson & Bettis-Outland, 2019). Therefore, we hypothesize:

H7. B2B marketing rational decision making has a positive relationship with firm performance.

3. Research methods

This section presents the research strategy of this study.

3.1. Sample selection

We used an online survey with samples from the mining and mineral processing industry in South Africa. The sample for the pilot survey and final survey was established based on random sampling from Directory No. D1/2016 "Operating mines and quarries and mineral processing plants in the Republic of South Africa, 2016" Directorate of Mineral Economics. This database was compiled by Ms. M C Lourens, and the 25th revised edition was published in January 2016 and considered in our study.

In WarpPLS two methods are used to estimate minimum required sample sizes, the inverse square root and gamma-exponential methods (Kock & Hadaya, 2018).

The "statistical power and minimum sample size requirements" analysis indicates 655 samples as per the inverse square root method; and 647 samples as per the gamma-exponential method. However, the research team selected the figure obtained from inverse square root method and further sent the online survey request to executive from every selected company and a total of 655 requests were sent out during the final survey.

3.2. Survey instrument

A structured questionnaire was used to collect the survey data. The questionnaire was based on a Likert-type scale (five points), where 1 means "strongly disagree"; 2 means "disagree"; 3 means "neutral"; 4 means "agree" and 5 means "strongly agree". The questionnaire was divided into two sections: Part A and Part B. The first part consisted of questions related to the role of the respondent, work experience, nature of business activities, number of employees in the company, age of the organisation and annual turnover. The second part consisted of questions related to BDAI, customer knowledge, user knowledge, external market knowledge, B2B marketing decisions and firm performance. The scale was developed based on past studies. For example, BDAI questions (11 items) were taken from Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Dubey, Gunasekaran & Childe, 2019, customer knowledge (8 items), user knowledge (6 items) and external market knowledge questions (4 items) were adapted from Paschen et al. (2019), B2B marketing decision questions (5 items) were taken from Daun et al. (2019) and firm performance questions (9 items) were adapted from Wamba et al. (2017) (refer to Appendix A).

The instrument was designed in consultation with other research team members from academia. Following the guidelines of Dillman (2011), background clearness of all the constructs was authenticated by two experts from academia. As per the suggestions of both experts, various changes were made to the questionnaire to suit this research study and the final version of the questionnaire was later approved by the same academic experts (Chen & Paulraj, 2004). The survey was then sent out to 75 executives working in different mining and mineral processing companies located in the Gauteng, North West, Mpumalanga and Limpopo provinces of South Africa. After 36 data points were received from the pilot survey, research team checked the reliability and validity parameters and found that the results were acceptable. The research team did not make any changes to the questionnaire based on the pilot survey.

3.3. Data collection

The invitation letter to fill in the questionnaire was e-mailed along with the online link to senior executives working in mines and mineral processing plants in South Africa. A total of 655 requests were made. After conducting follow-up, 306 completed questionnaires (response rate of 46.71%) was received. The research team did not receive any incomplete questionnaires, as the settings in the google form-based questionnaire did not allow for this, and a warning would pop up with a note to prevent any duplicate or incomplete submissions. The details of the respondents and their organisations are provided in Table 1.

3.4. Common method variance

Online surveys in marketing research are often criticised for attracting common method variance (CMV) problems (Hulland, Baumgartner, & Smith, 2018). Few key problems were identified as vital elements of survey validity: perform pretesting to make sure that good quality survey instruments are used; considering use of multi-item scales with strong psychometric properties to control measure unreliability; the use of research design elements that a priori assist to lower CMV; and considering tests to account post hoc for common method bias (Hulland et al., 2018).

Table 1
Details of respondents and their organisation.

Details	Respondents	(In Number)	(In Percentage)
Designation	General Manager	45	14.70
	Senior Manager	207	67.64
	Manager	25	8.16
	Junior Manager	29	9.47
Experience (Years)	Above 20	77	25.16
	10 to 20	185	60.45
	Below 10	44	14.37
Nature of Business Activities	Mines, Quarries and allied industries	145	47.38
	Mineral processing and allied industries	161	52.61
Age of the Firm (Years)	Above 20	272	88.88
	10 to 20	28	9.15
	5 to 10	6	1.96
	Below 5	0	0.00
Annual Turnover (South African Rands)	< R10 million	0	0.00
	<R50 million	0	0.00
	>R50 million	306	100.00

Source: Authors' own compilation.

Post hoc methods for avoiding common method variance problems include Harman's single factor test, partial correlation procedures controlling for CMV at the scale level, use of a directly measured or single unmeasured (latent) method factor to account for CMV at the item level, and use of multiple method factors to correct for CMV (Hulland et al., 2018).

Research team therefore took the utmost care and necessary precautions from the beginning of the survey to avoid any such problems. First, the research team drafted an invitation letter for the survey stating the reason the survey was being conducted and also indicating that participants can stop the survey at any time if they no longer wish to complete the survey. The system would not allow incomplete questionnaires to be submitted. Second, all the questions were drafted in simple English and relevant to the industry so that readers would be spared from any confusion. Third, all of the questions involved simply ticking the response and did not include any writing. The questions were divided into two parts for easy understanding and finally, the questionnaire was kept short to prevent the survey participants from losing patience. Research team also performed post-hoc test and calculated the Harman's one factor test. The results indicated that a single factor accounts for 24.587% of total variance, which is far less than 50%. Therefore, it can be concluded that there is no danger of CMV (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Typically, researchers do not worry much about method bias in PLS because PLS often focuses on formative factors. Formative factors very rarely suffer from method bias. The article written by Ned Kock suggests about dealing with method bias in PLS (Kock, 2015; Kock, 2020). As per the Kock (2020) full collinearity VIFs can be considered for CMV tests. This is better than the traditional tests conducted by researchers using EFA. PLS-based SEM recommends threshold value of full collinearity VIF should be 3.3 or below to avoid multicollinearity and CMV problems. Findings indicate that the full collinearity VIF for latent variables is below the threshold value and it is proved that CMV is not an issue in this study.

3.5. Non-response bias

The primary data was received in two phases. One set of responses was received before follow-up and the second set was received after doing follow-up with the potential respondents. The early wave (120 responses) and the late wave (186 responses) were compared using Levene's test to check for non-response bias (Armstrong & Overton, 1977). Levene's homogeneity of variance test was conducted to check whether the distribution of our variables changed depending on the wave. SPSS software was used to compare means and perform the analysis by selecting one-way ANOVA to check the Levene statistic. The research team found that none of the values were significant, which means there was no difference between the waves.

4. Data analysis and findings

4.1. Partial least square-based structural equation modelling

Multivariate data analysis (MDA) has been shown to be useful in evaluating relationships among numeric variables while simultaneously controlling for the impact of other variables (Hair, Anderson, & Tatham, 1987). Multiple regression, path analysis and structural equation modelling (SEM) are the most commonly used MDA techniques. Furthermore, SEM is divided into two categories: covariance-based SEM (CB-SEM) and variance-based SEM. Variance-based SEM is also known as PLS-SEM. The benefits of PLS-SEM are: a) mainly getting a solution, even for complex models; b) it is not essential for variables to conform to parametric analysis conditions, for example, normality and larger sample size; c) it makes it possible to estimate parameters that have multiple formative latent variables and to assess moderating effects (Kock, 2010). The research team decided to use partial least square-based structural equation modelling (PLS-SEM). WarpPLS software was chosen to run the analysis. WarpPLS was invented by Ned Kock (Kock, 2012), and as the software is very user friendly, it has become quite popular in a very short period of time. WarpPLS-based analysis has been used previously by leading researchers in the field of management, and their work has been accepted in top ranked journals (e.g., Dubey, Gunasekaran, & Childe, 2019, Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Wamba et al., 2017). Scientific debate over the use of CB-SEM or PLS-SEM is still ongoing. However, simple guidelines were set forth by Preacher and Hayes (2004) and Hair Jr, Matthews, Matthews, and Sarstedt (2017) to select the right technique depending on the nature of the research work. The research team met the criteria as suggested by Hair Jr et al. (2017) to proceed with the use of PLS-SEM. In the next stage, research team checked the reliability and validity of the measurement model based on the suggestions of Peng and Lai (2012).

4.2. Measurement model

Before checking the results of the hypothesis testing, research team checked the VIF value, as it helps identify the presence of data multicollinearity. The findings indicated that the average full collinearity VIF was 2.746. This is acceptable, as it should be less than 5. Ideally it should be lower than 3.3, and our value is much lower than the ideal value. It can therefore be stated that there are no multicollinearity issues in this work. Research team also checked the model fit indices and found them to be significant. The goodness of fit value shows a large fit (see Table 4).

The causality assessment indices employed (see Kock, 2020) were the Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), statistical suppression ratio (SSR) and nonlinear bivariate causality direction ratio (NLBCDR). They are within the threshold values and rule out any endogeneity problems (Kock, 2015) (see Table 2).

Composite reliability shows BDAI (0.893), CUK (0.821), USK (0.794), EMK (0.844), BMD (0.842) and FIP (0.922) values are higher than 0.70, and their AVE values are above 0.50. The results indicate that the reliability of all the constructs accounts for 50% variance in their related items. Combined loadings and cross-loadings were found to be above 0.50 (refer to Appendix B).

Discriminant validity was checked (see Table 3) and the research team established discriminant validity by following the Fornell-Larcker criterion, i.e. for any latent variable, the square root of the AVE must be higher than its correlation with any other latent variable (Kock, 2020). The results suggest that our measurement model displays acceptable discriminant validity.

Cronbach's alpha yielded the following values: BDAI (0.866), CUK (0.750), USK (0.683), EMK (0.747), BMD (0.765) and FIP (0.902). The values indicate that they are reliable.

Table 2
Model fit and quality indices.

Model fit and quality indices
Average path coefficient (APC) = 0.456, P < .001
Average R-squared (ARS) = 0.530, P < .001
Average adjusted R-squared (AARS) = 0.528, P < .001
Average block VIF (AVIF) = 5.131, acceptable if ≤ 5, ideally ≤ 3.3
Average full collinearity VIF (AFVIF) = 2.746, acceptable if ≤ 5, ideally ≤ 3.3
Tenenhaus GoF (GoF) = 0.575, small ≥ 0.1, medium ≥ 0.25, large ≥ 0.36
Sympson's paradox ratio (SPR) = 1.000, acceptable if ≥ 0.7, ideally = 1
R-squared contribution ratio (RSCR) = 1.000, acceptable if ≥ 0.9, ideally = 1
Statistical suppression ratio (SSR) = 1.000, acceptable if ≥ 0.7
Nonlinear bivariate causality direction ratio (NLBCDR) = 0.833, acceptable if ≥ 0.7

Source: WarpPLS output.

Table 3
Discriminant validity test results.

	BDAI	CUK	USK	EMK	BMD	FIP
BDAI	**0.665**	0.531	0.419	0.546	0.544	0.414
CUK	0.531	**0.627**	0.424	0.449	0.571	0.440
USK	0.419	0.424	**0.684**	0.767	0.554	0.347
EMK	0.546	0.449	0.677	**0.768**	0.641	0.502
BMD	0.544	0.571	0.554	0.641	**0.720**	0.718
FIP	0.414	0.440	0.347	0.502	0.718	**0.760**

Source: WarpPLS output.

4.3. Results

The hypothesis assessment findings are presented in Fig. 2. The findings show that there is a positive relationship between BDAI →CUK (β = 0.67), BDAI →USK (β = 0.51), BDAI →EMK (β = 0.60), CUK → BMD (β = 0.27), USK → BMD (β = 0.38), EMK → BMD (β = 0.86) and BMD → FIP (β = 0.72). Statistical significance was considered at 5% as the cut-off value for accepting/not accepting research hypotheses. All hypotheses were supported except the effect of two control variables which were found to be non-significant.

The results of hypotheses testing are presented in Table 4.

5. Discussion

Information technology-based applications are gaining importance in designing intelligent products for human usage (Shareef et al., 2021). Marketers can benefit significantly by adopting AI and VR technologies (Dwivedi et al., 2020). AI is the new electricity in this digital age (Grover, Kar, & Dwivedi, 2020). AI based intelligent systems have the power to support strategic decision making, where strategic intelligence is necessary (Martínez-López & Casillas, 2013). However, there are limited research studies in this domain (Pandey et al., 2020; Pillai, Sivathanu, & Dwivedi, 2020). Hence, this study aims to establish that "big data powered artificial intelligence" acts as a knowledge management enabler that drives "knowledge management process" i.e. customer knowledge creation, user knowledge creation and external market knowledge creation. These three dimensions of knowledge management process play a critical role in B2B marketing decision making style which will enhance the firm performance.

Bacharach (1989) defined theory as a statement of links among ideas within a boundary set of assumptions and constraints. The aim of a theoretical statement is to organize (parsimoniously) and to communicate (clearly).

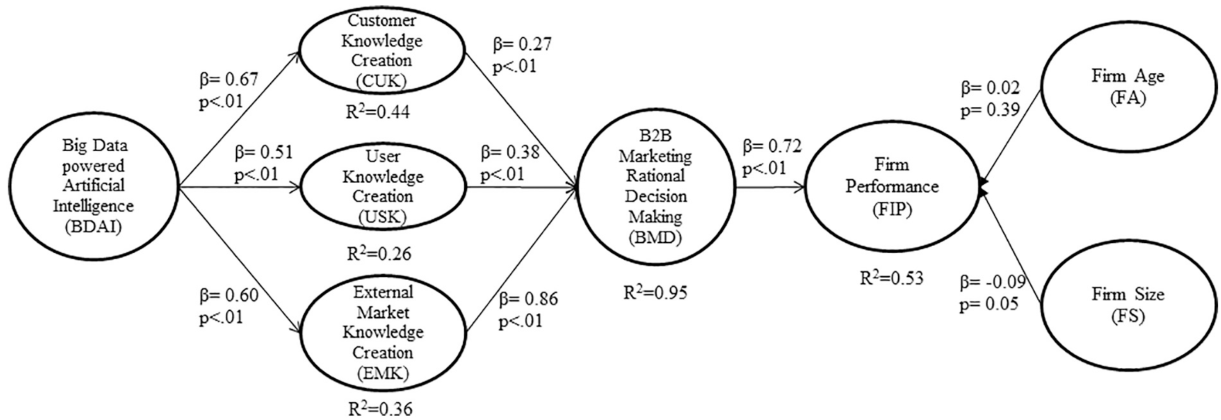

Fig. 2. Model after PLS-SEM analysis.

Table 4
Summary of hypotheses testing.

No.	Hypotheses	β and p-value	Outcome
H1	Big data powered artificial intelligence has a positive relationship with customer knowledge creation	β = 0.67, p < .01	Supported
H2	Big data powered artificial intelligence has a positive relationship with user knowledge creation	β = 0.51, p < .01	Supported
H3	Big data powered artificial intelligence has a positive relationship with external market knowledge	β = 0.60, p < .01	Supported
H4	Customer knowledge creation has a positive relationship with B2B marketing rational decision making	β = 0.27, p < .01	Supported
H5	User knowledge creation has a positive relationship with B2B marketing rational decision making	β = 0.38, p < .01	Supported
H6	External market knowledge creation has a positive relationship with B2B marketing rational decision making	β = 0.86, p < .01	Supported
H7	B2B marketing rational decision making has a positive relationship with firm performance	β = 0.72, p < .01	Supported

Further, Wacker (2008) stressed that academic research focuses on theory building. Good theories can be used to understand specific situations. Researchers need to enhance theory to make a theoretical contribution (Reay & Whetten, 2011). The fundamental building blocks of theory necessitates that researchers search answers for the four questions i.e. what are the main elements that are important to the elucidation of the phenomenon of attention? How are these main elements linked with one another? Why does this depiction of the phenomenon justify to be considered reliable? What are the settings under which researcher ought to assume the predictions of the theory to hold correct?

Byron & Thatcher (2016) provided recipes for making theory building and making theoretical contributions. Using KMT theory as a theoretical lens the research team answered two research questions in this study.

RQ1. Can big data powered AI enhance knowledge creation in B2B marketing? and RQ2: Can knowledge creation improve B2B rational marketing decision making and further enhance firm performance?

The results indicate that the path "big data powered artificial intelligence and customer knowledge creation" is significant. Hence, H1 is supported. Second, the path "big data powered artificial intelligence and user knowledge creation" is significant which supports H2. Third, "big data powered artificial intelligence and external market knowledge creation" is significant which supports H3. Fourthly, the path "customer knowledge creation and B2B marketing rational decision making" was found to be significant and H4 was supported. Fifth, the path "user knowledge creation and B2B marketing rational decision making" was found to be significant and H5 was supported. Sixth, the path "external market knowledge creation and B2B marketing rational decision making" was found to be significant and H6 was supported. Finally, the path "B2B marketing rational decision making and firm performance" was found to be significant. Hence, H7 was supported.

It is clear from the findings that AI is changing the marketing landscape as previously indicated by Davenport et al. (2019). Mining industry operations are complex and face many challenges related to energy access, strict health and safety regulations, capital, commodity price volatility and the environmental footprint, which makes the buying and selling processes for mining companies very complex and strict (Hamann, 2003). Marketers who deal with mining companies therefore face many barriers when conducting B2B transactions. Mining and mineral processing companies tend to use sustainability practices to enhance business performance (Gomes, Kneipp, Kruglianskas, da Rosa, & Bichueti, 2014). Marketers need to consider sustainability parameters in their product and service offering while dealing with mining and mineral processing companies. The current research applied Knowledge Management theory to better understand the ways B2B marketers leverage big data to empower AI, and the empirical testing of the theoretical model has yielded insights that can potentially make rich theoretical contributions. Big data powered AI enhances customer knowledge creation, user knowledge creation and external market knowledge creation, which further improves B2B marketing rational decision making and finally improves firm performance. Although these findings are supported by the work of Paschen et al. (2019) but current research findings offer some interesting insights such as the impact of BDAI on customer knowledge creation is found to be much stronger than the impact of BDAI on external knowledge creation and user knowledge creation. It is therefore clear that B2B marketers in South African mining and mineral processing industry prefer to leverage BDAI and use structured and unstructured data of different nature and perform analysis related to attitude and behaviour of customers. In addition, machine learning and predictive analytics tools are increasingly used to create profile of future customers and develop relationship strategy accordingly. It was found that external market knowledge creation has more impact on B2B marketing rational decision making than customer knowledge creation, user knowledge creation.

Finally, the results indicate that B2B marketing rational decision making is very important for the strong performance of firms. Syam and Sharma (2018) and recently Dwivedi et al. (2019) have rightly pointed out that the fourth industrial revolution will be disrupted by artificial intelligence powered by big data technology. These advanced technologies will impact B2B marketing and sales management (Davenport et al., 2019). The theoretical contributions and implications of current study findings is presented below.

5.1. Theoretical contributions and implications

This study tested the theoretical model by drawing on KMT. Knowledge management can be used to deal with the diffusion and development of knowledge and to analyse the knowledge features of a relationship in order to handle it more efficiently (Powell & Swart, 2010). Knowledge is an amalgamation of contextual information, the experience of experts and value that can result in innovation (Abubakar et al., 2019).

The theoretical model in this study is unique which further provided some testable hypotheses. The research team tested KMT theory in context to B2B marketing and sales. In such process it has contributed to the existing literature from two aspects. First, the power of digital technology (BDAI) has been established in this work which basically acts as knowledge management enabler. Second, this research has established that knowledge management process including customer knowledge creation, user knowledge creation and external market knowledge creation is very important for B2B rational decision making. Hence, this study extends the knowledge base by clearly indicating the importance of digital technology-based knowledge enabler in creating knowledge and improving B2B decision making for enhancing organisation performance.

5.2. Practical implications

The digital disruption has changed the work flow and processes in organisations. Information and communication technologies (ICT) are playing a critical role in the success/failure of a business. In Africa the mining and minerals processing business operates in a volatile environment. B2B marketers face lot of challenges while working in such environments. Advanced ICT technologies can not only help in capturing the market information but also provides important details of the plant operations that can be help in designing of right products and solutions. Top management can leverage advanced ICT to track the day-to-day sales calls and meetings made by every sales person. The sales team can capture the meeting related details on their tablet/mobile phone using some special apps. They can as well highlight the need for management intervention, if any. Problems are solved much faster resulting in increased efficiency.

Not only that the analysis of large data sets can also be useful for understanding customers buying patterns, sentiments and attitudes towards particular brands. Further AI can be used to provide support to the B2B marketers. Therefore, B2B marketers can leverage big data powered AI to enhance knowledge management process much better in this I4.0 era. Knowledge management is important to progress forward and enhance business performance. From a realistic point of view, a few of our study's takeaway points can be of use to marketing executives. First, senior leaders need to pay proper attention to big data that can help harness AI and generate value. Second, it is essential to focus on knowledge management processes involving customer knowledge creation, user knowledge creation and external market knowledge creation in order to make B2B marketing rational decisions. Finally, the quality of B2B marketing decisions must be high, as they influence firm performance.

Our findings indicate that important BDAI features include access to large, unstructured and fast-moving data for analysis, the integration of external and internal data for analysis, the Hadoop platform for analysis, BDAI training and collaboration with DTI and universities. Firms need to focus more on these BDAI enablers in particular.

The findings also indicate that in the CUK-related group, AI presentation bots that can assist sales teams in making convincing presentations are gaining more popularity. In the user knowledge category, however, two items are making more impact than the others: first, the capabilities of AI to understand emotions, values and attitudes in a text, and second, the ability of AI to recognise patterns in customer posts and their attitudes towards a particular product, which can in fact provide a great deal of valuable information for knowledge management. When it comes to external knowledge management, the two items that created the greatest impact are the ability of AI to gather business intelligence related to competitors and other stakeholders, and the ability of AI to exploit market knowledge by analysing unstructured big data sets from various sources. This can enhance the knowledge management process in B2B marketing.

The findings reveal that most important B2B marketing rational decisions are related to BDAI based expert systems to support decision making at strategic, operational and tactical levels. Second, the knowledge gained from BDAI application can keep firms up-to-date in terms of their current position compared to their competitors and help advance new product innovations. Finally, knowledge generated through BDAI based applications can help B2B marketers to be cautious about their brands and eliminate any threats that arise from fake news.

In terms of the impact of B2B marketing rational decisions on firm performance, the greatest benefits actually include better customer retention, penetration in new markets and the quick launch of new products. This study therefore advances the use of KMT in the field of B2B marketing.

5.3. Limitations and future research direction

The research team have taken the necessary precautions to avoid any kind of bias during data collection and checked all parameters before proceeding with data analysis. The study was conducted among South African-based companies involved in B2B business in the mining and mineral processing industry, and readers/researchers must therefore interpret the findings in light of the context. AI applications are currently in the nascent stage, and future researchers can explore the outcome of collaborative relationship aspects (supplier collaboration, human and machine collaboration, collaboration with project teams and universities) on AI and firm performance. Institutional mechanisms to drive big data and artificial intelligence in the digital age require further investigation. Privacy is a big concern when using big data and artificial intelligence, particularly in B2B marketing. Customer fears concerning the sharing of personal data can impede the application of BDAI and prevent it from unlocking the value of big data. Research is needed on the development of BDAI policies to safeguard against data misuse by B2B marketers. Finally, B2B and triple bottom line research need more attention from future researchers.

6. Conclusion

This study is focused on the potential of BDAI to unlock value based on customer knowledge, user knowledge and external market knowledge. The theoretical model was grounded in KMT and involves BDAI (knowledge management enabler), customer knowledge creation, user knowledge creation and external market knowledge creation (knowledge management process), B2B marketing rational decisions (decision making style) and firm performance (organisation output) in line with the study by Abubakar et al. (2019). This research work highlights the requirements of and creates a model for knowledge management and decision making related to B2B marketing in this digital age. The model demonstrates the impact of the knowledge management enabler (BDAI) on the knowledge management process for B2B marketing decisions. The key findings are: big data powered artificial intelligence have a positive relationship with customer knowledge creation. Second, big data powered artificial intelligence have a positive relationship with user knowledge creation. Third, big data powered artificial intelligence have a positive relationship with external market knowledge creation. Fourth, customer knowledge creation has a positive relationship with B2B marketing rational decision making. Fifth, user knowledge creation has a positive relationship with B2B marketing rational decision making.

Sixth, external market knowledge creation has a positive relationship with B2B marketing rational decision making. Finally, B2B marketing rational decision making have a positive relationship with firm performance. The paths are unique and highlight that knowledge management using BDAI is important for B2B marketers to survive in this competitive environment. In this process, this study advances the theoretical debate surrounding AI application in B2B decision making.

Appendix A. Operationalization of constructs

Constructs	Code	Items	Adapted from
Big data powered Artificial intelligence (BDAI)	BDAI1	Our organisation has access to unstructured and structured data sets	Dubey, Gunasekaran, & Childe, 2019, Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019)
	BDAI2	Our organisation amalgamates internal and external data for value analysis business environment	
	BDAI3	We apply advanced analytical techniques for decision making	
	BDAI4	We use computing techniques (e.g. Hadoop) for processing of large data sets	
	BDAI5	We use data visualization methods to decode complex data	
	BDAI6	Our management have approved budget for big data and artificial intelligence project	
	BDAI7	We give BDAI training to our employees	
	BDAI8	We appoint persons having long experience in handling BDAI	
	BDAI9	We have collaborated with DTI and Universities for implementing BDAI projects	
	BDAI10	Our BDAI team coordinate effectively with other departments and stakeholders	
	BDAI11	AI bots can assist sales team by automating certain steps of sales and improving capabilities of sales force	
Customer Knowledge Creation (CUK)	CUK1	BDAI can be used to utilise structured and unstructured data of different nature and perform analysis related to attitude and behaviour of customers	Paschen et al. (2019)
	CUK2	Machine learning and predictive analytics tools can be useful to create profile of future customers and develop relationship strategy accordingly	
	CUK3	BDAI can improve every process involved in B2B sales activity	
	CUK4	AI can be used to identify prospects	
	CUK5	AI can automate sales process and schedule meetings and further answer common questions	
	CUK6	AI presentation bots can assist B2B sales force in making mind blowing presentations	
	CUK7	AI can be useful in convincing customers and beat customers by improving own value offerings	
	CUK8	AI can be useful in automatic order follow-ups and order processing	
User Knowledge Creation (USK)	USK1	User knowledge is important for developing new products and enhancing creativity	Paschen et al. (2019)
	USK2	AI can perform content analysis and provide insights about users' likings and disliking	
	USK3	The AI system can understand emotions and attitudes in a text	
	USK4	Psychographic characteristics can be a valuable source of insight for B2B marketers in development of new products	
	USK5	AI can be used to identify themes and patterns in social media post related to product buying and their product use experiences	
	USK6	AI-enabled knowledge about users may indicate how users modify some products themselves and such information can be helpful for new product developments	
External Market Knowledge Creation (EMK)	EMK1	BDAI can be used to gather intelligence about external market forces and stakeholders	Paschen et al. (2019)
	EMK2	BDAI enables external market knowledge	
	EMK3	AI systems using NLP and ML algorithms are more and more used to examine and identify fake news content	
	EMK4	AI can enable B2B marketers develop competitive intelligence	
B2B Marketing Rational Decision Making (BMD)	BMD1	AI is believed to be able to help organisational employees to make better decisions and improve creativity	Duan et al. (2019)
	BMD2	AI based expert systems in a support role can help users make good decisions	
	BMD3	This insight gained through AI based knowledge creation can be useful in understanding firm's current position against competitors	
	BMD4	This insight gained through AI based knowledge creation can caution marketers to remain alert about their brands and identify fake news that can cause harm to the brand	
	BMD5	AI technology enables in undertaking complex work and make sound judgements	
Firm Performance (FIP)	FIP1	Our firm is able to retain customers much better than competitors	Wamba et al. (2017)
	FIP2	Sales increase has happened in our firm	
	FIP3	Our firm is able to achieve high profit margins	
	FIP4	Return on investment is higher in our firm	
	FIP5	Overall financial performance has improved in our firm	
	FIP6	We have entered new markets more quickly than our competitors	
	FIP7	We have introduced new products or services to the market faster than our competitors	
	FIP8	Our success rate of new products or services has been higher than our competitors	
	FIP9	Our market share has exceeded that of our competitors	

Appendix B. Combined loadings and cross loadings

	BDAI	CUK	USK	EMK	BMD	FIP	SE	P value
BDAI1	**0.605**	−0.323	0.062	−0.113	−0.074	0.121	0.052	<0.001
BDAI2	**0.792**	−0.254	0.301	−0.348	−0.031	0.079	0.051	<0.001
BDAI3	**0.750**	−0.152	0.490	−0.453	−0.148	0.076	0.051	<0.001
BDAI4	**0.547**	−0.067	−0.266	0.296	0.493	−0.405	0.053	<0.001
BDAI5	**0.756**	−0.148	−0.185	0.232	0.221	−0.224	0.051	<0.001
BDAI7	**0.764**	−0.166	−0.156	0.149	−0.226	0.078	0.051	<0.001
BDAI8	**0.790**	−0.006	0.002	0.137	−0.330	0.245	0.051	<0.001
BDAI9	**0.728**	0.064	−0.076	0.289	−0.192	0.082	0.051	<0.001
BDAI10	**0.522**	0.492	−0.697	0.586	0.749	−0.485	0.053	<0.001
CUK1	−0.115	**0.733**	0.224	−0.112	−0.088	0.318	0.051	<0.001
CUK2	−0.032	**0.834**	−0.343	0.200	0.091	−0.172	0.050	<0.001
CUK3	−0.124	**0.736**	0.222	−0.115	−0.090	0.305	0.051	<0.001
CUK4	−0.023	**0.826**	−0.378	0.235	0.079	−0.176	0.050	<0.001
CUK5	−0.084	**0.578**	0.393	−0.481	−0.181	−0.019	0.052	<0.001
USK3	−0.041	0.011	**0.860**	−0.226	0.025	0.048	0.050	<0.001
USK5	−0.074	−0.033	**0.946**	0.435	−0.096	−0.045	0.049	<0.001
USK6	−0.101	−0.011	**0.948**	0.377	−0.077	−0.046	0.049	<0.001
EMK1	−0.123	−0.003	0.629	**0.874**	−0.077	−0.060	0.050	<0.001
EMK2	0.083	−0.039	0.002	**0.917**	−0.114	−0.159	0.050	<0.001
EMK3	0.160	0.016	−0.710	**0.748**	0.122	−0.250	0.051	<0.001
BMD1	0.413	−0.250	0.157	0.068	**0.606**	0.199	0.052	<0.001
BMD2	−0.006	0.114	0.337	−0.368	**0.674**	0.323	0.051	<0.001
BMD3	−0.205	−0.158	−0.008	−0.164	**0.736**	0.494	0.051	<0.001
BMD4	−0.112	0.290	−0.166	0.321	**0.770**	−0.471	0.051	<0.001
BMD5	−0.012	−0.040	−0.236	0.101	**0.797**	−0.426	0.051	<0.001
FIP1	−0.086	0.001	−0.113	−0.024	0.067	**0.773**	0.051	<0.001
FIP2	−0.167	0.004	−0.090	−0.031	0.161	**0.862**	0.050	<0.001
FIP3	−0.194	0.032	−0.052	−0.013	0.177	**0.923**	0.050	<0.001
FIP4	−0.157	0.056	−0.269	0.109	0.166	**0.893**	0.050	<0.001
FIP5	−0.205	0.044	−0.080	0.020	0.187	**0.929**	0.049	<0.001
FIP6	0.306	−0.076	−0.541	0.590	−0.033	**0.616**	0.052	<0.001
FIP7	0.328	−0.101	−0.178	0.450	−0.200	**0.579**	0.052	<0.001
FIP8	0.304	−0.026	0.839	−0.582	−0.504	**0.548**	0.052	<0.001
FIP9	0.304	−0.008	0.878	−0.633	−0.461	**0.574**	0.052	<0.001

Source: WarpPLS output.

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