Unpacking artificial intelligence – How the building blocks of artificial intelligence (AI) contribute to creating market knowledge from big data[1]

Abstract

Purpose:

This study explains artificial intelligence (AI) and its contributions to creating market knowledge from big data. Specifically, this study describes the foundational building blocks of any AI technology, their interrelationships and the implications of different building blocks with respect to creating market knowledge, along with illustrative examples.

Design/methodology/approach:

The study is conceptual and proposes a framework to explicate the phenomenon AI and its building blocks. It further provides a model of how AI contributes to creating market knowledge from big data.

Findings:

The study explains AI from an input–processes–output lens and explicates the six foundational building blocks of AI. It discusses how the use of different building blocks transforms data into information and knowledge. It proposes a conceptual model to explicate the role of AI in creating market knowledge and suggests avenues for future research.

Practical implications

This study explains the phenomenon artificial intelligence, how it works and its relevance for creating market knowledge for B2B firms.

Originality/value:

The study contributes to the literature on market knowledge and addresses calls for more scholarly research to understand AI and its implication for creating market knowledge.

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[1] An amended version of the manuscript has since been published in a peer-reviewed journal.

Keywords:
Market knowledge, B2B marketing, Artificial intelligence, Machine learning, Natural language processing, Big data

Paper type:
Conceptual paper

Introduction

Scholars from a variety of disciplines agree that businesses are no longer seen from an industrial, but from a knowledge perspective (Grant, 1996, 2002; Spender & Grant, 1996). Knowledge, gained from superior information quantity and quality, has become the dominant resource and outpaced physical and financial capital in terms of its organizational importance (Archer-Brown & Kietzmann, 2018; Bollinger & Smith, 2001; Drucker, 1999).

Knowledge is also at the heart of market orientation (Day, 1990, 1994, 2000) which has been a dominant marketing paradigm since the 1990s. In particular, market knowledge (Kohli & Jaworski, 1990) is critical for creating offerings that cater to the needs and preferences of customers and for ultimately building and maintaining effective long-term customer relationships. Thus, the creation and use of market knowledge can translate into effective B2B marketing strategies and tactics (Shaw *et al.*, 2001).

In recent years, the increasing digitalization and the advent of emerging information and communication technology has transformed value creation in B2B in general, and more specifically, how B2B firms manage data and knowledge (Gupta *et al.*, 2017). First, information and communication technologies have fueled the creation of large volumes of data, for example, from the almost ubiquitous use of social media (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011) and the rise of the Internet of Things (IoT) (Osmonbekov & Johnston, 2018; Robson *et al.*, 2016; Turunen *et al.*, 2018). Individually, these new and still emerging data points mean little when compared to their profound joint meaning (Pigni *et al.*, 2016). Collectively, big data, vast in terms of their volume, velocity, variety, veracity and value (known as the Five V’s), are becoming an increasingly valuable source for market knowledge for B2B companies.

Second, emerging information technologies can help companies uncover, organize and share the knowledge contained in big data (Codini *et al.*, forthcoming). One information technology that is gaining increased interest among practitioners is artificial intelligence (AI) (Martínez-López & Casillas, 2013; Singh *et al.*, 2019; Syam &

Sharma, 2018). For example, the professional services sector ranked among the top sectors to embrace AI (MIT Technology Review Insights, 2018). The premise is that, for B2B companies, AI can help translate (big) data into information and into knowledge required for developing effective marketing and sales strategies and tactics. Traditionally, this has been a difficult undertaking in B2B marketing, where B2B marketers need to focus on both, understanding customers, i.e., those who make the buying decision, in addition to understanding the consumers, i.e., those who consume or use the offering (Abrell *et al.*, 2016). The potential impact that practitioners expect AI to offer to the B2B marketing and sales practice include personalization, customization, innovation and enhanced marketing effectiveness and efficiencies (EverString, 2018).

While marketers acknowledge the opportunities for AI-enabled knowledge, there appear to be gaps in comprehensively understanding AI and how to operationalize it for B2B marketing processes and decision making (Martínez-López & Casillas, 2013; Singh *et al.*, 2019; Syam & Sharma, 2018). In other words, when B2B marketers discuss AI, they often refer to and use different terms and concepts, thereby leading to misunderstandings and confusion about what AI can and cannot do. In order for B2B managers and executives to be able to assess AI properly, a first critical step is to understand what AI is, what the different related terms and concepts mean and how they all come together to offer different value propositions to B2B marketing. In addition, there is a gap in understanding on the implications of AI with respect to market knowledge in a B2B context.

This study addresses both of these gaps. In response to the first, this study describes the foundational building blocks of AI and their interrelationships, in addition to clarifying AI-terminology that is often used interchangeably in practice. With respect to the second gap, this study discusses the implications for AI with respect to different types of market knowledge in the context of B2B marketing decision making and outlines avenues for future research in this area. In doing so, this study contributes to the literature on AI and B2B marketing from a knowledge perspective, while addressing the call for more scholarly work in this area (see Martínez-López & Casillas, 2013; Singh *et al.*, 2019; Syam & Sharma, 2018).

The remainder of this study proceeds as follows. Section 2 begins with a conceptual clarification of artificial intelligence information technology, grounding the concept in the appropriate literature. Next, this study describes the foundational building blocks of artificial intelligence and their interrelationships, along with illustrative examples from B2B marketing. Section 4 discusses the implications of AI for market knowledge in B2B marketing along with avenues for future scholarly research, before concluding with a summary of implications.

Defining artificial intelligence

Intelligence, in the human context, is defined as a person's ability to learn, to deal with new situations, to understand abstract concepts, and use knowledge to manipulate one's environment (Legg & Hutter, 2007; Sternberg, 2017). In more general terms, intelligence is defined as the ability to perceive and process data, transform data into information and ultimately knowledge, and use this knowledge towards goal-directed behavior. Effective adaptation of intelligence draws upon the selective combination of a number of processes, including perceiving one's environment, problem solving, reasoning, learning, memory and acting to achieve goals.

Following extant conceptualizations, artificial intelligence is defined as "computational agents that act intelligently" (Poole & Mackworth, 2010, p. 3). This definition departs from previous views that AI is about machines that can display human-like intelligence in two important ways. First, it focuses on acting intelligently which refers to performing the above outlined processes, such as perception, learning, memorizing, reasoning, and problem solving towards goal-directed behavior. This conceptualization evaluates the performance of AI not in terms of conformity to human behavior, but instead in terms of an ideal performance called rationality (Russell & Norvig, 2016). AI is rational if it does the "right thing", given what it knows. A rational view suggests that AI acts to achieve the best outcome or, when there is uncertainty, the best expected outcome. By distinguishing between human and rational behavior, it is not suggested that humans are necessarily irrational, but simply note that human behavior sometimes encompasses behavior that may not achieve the best final outcome (Kahnemann & Tversky, 1979) due to people's limited information, cognitive abilities, emotions or intuition.

The second key element in the notion of AI is “computational agents”. Referring again to Russell and Norvig (2016), in information systems, an agent perceives its environment and acts upon this environment. Human agents perceive through their eyes, ears, and other organs, and act using their hands, legs, or vocal tracts. Computer agents use sensors to perceive inputs and act on the environment by writing files, moving objects, or displaying output on a screen. Thus, by including the notion of computational agents, it is suggested that AI agents solve problems in practice as opposed to only in principle.

It should be noted that every single AI application described here falls into the field of “narrow” AI, rather than “strong” AI. Narrow artificial intelligence describes AI technologies that are optimized for a given task. On the other hand, strong AI, also known as “artificial generalize intelligence”, is the research and practice of technologies capable of solving any intellectual task, much like a person can. This is extremely difficult, and currently does not exist in practice. The uses of AI discussed in this study focus on narrow AI technologies.

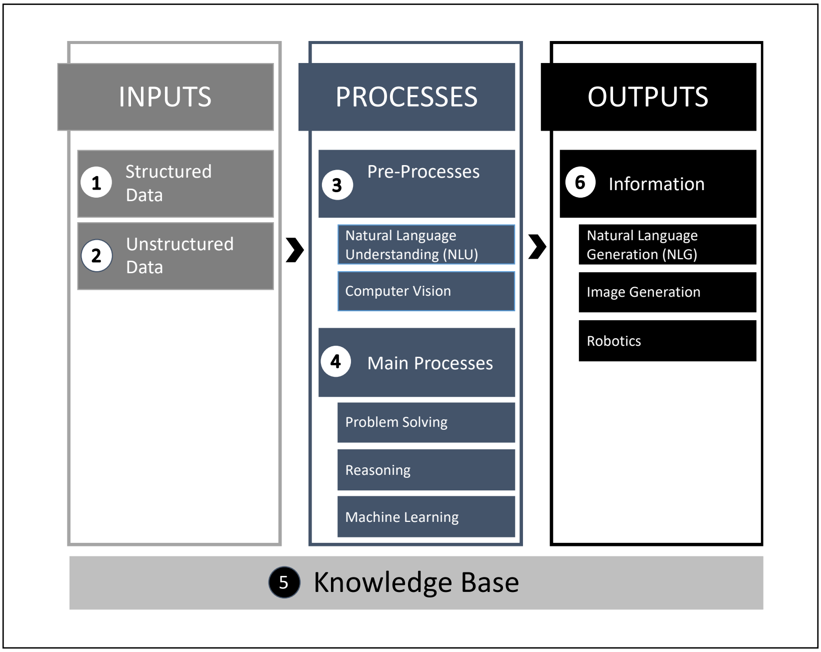
Information technologies, at any level of sophistication or intelligence, consist of hardware (e.g., computers, servers), software (e.g., algorithms), data (e.g., collections of facts, numbers), and procedures (e.g., rules or descriptions for how to use, operate, or maintain an information technology) (Silver *et al.*, 1995). The interaction of information technologies with their organizational and social environment follows a basic input-process-output model in which the technology itself is seen as a separate entity from its environment. Accordingly, the technology requires data from human or physical sources in their environment (inputs), manipulates such data in value-creating ways (processes), and feeds information (outputs) back to the environment.

It is important to distinguish between data, information and knowledge. Data are treated as raw facts that represent a subject or object in the real world but does not have meaning. Census holders collect data about households; marketers collect data about customer demographics. Information emerges when data is processed so it has meaning and purpose. For example, marketers may process customer demographics to create different target market segments. Knowledge is information that has been combined with experience, skill and expertise and is context specific (Davenport *et al.*, 1998; Davenport & Prusak, 1998).

The six building blocks of artificial intelligence

The previous section clarified artificial intelligence conceptually based on the extant literature. Having defined the two key constructs, artificial intelligence and information technologies, this section unpacks AI into six building blocks as illustrated in Figure 1: structured data, unstructured data, pre-processes, main processes (i.e., problem solving, reasoning, machine learning), knowledge base, and information. The following section offers an introduction to and a definition of each building block (in italics) and discusses each building block's role in AI.

Figure 1 Artificial intelligence - building blocks and their interrelationships



Inputs

Inputs are the data that is perceived and collected from the environment. For AI, these inputs come in two forms: structured and unstructured data.

AI Building Block 1: Structured Data
Structured data are data that are standardized and organized according to predefined schema. They form the heart of business analytics and business intelligence - activities that are concerned with the methodical exploration of an organization's structured data, often with a strong emphasis on quantitative analyses. Examples include customer demographics, web browsing data or transaction data – all these are internal structured data – and social media ratings or stock exchange transactions, which are examples of external structured data. AI, powered by growing computational efficacy and rapidly improving machine learning techniques (explained in building block 4), is able to run computations on different types of structured data, often in real time.

AI Building Block 2: Unstructured Data
Unstructured Data are data that are not standardized or organized according to a pre-defined schema. What sets AI apart from traditional information technologies is that it can also handle the vastly increasing amount of input data that come in unstructured formats. IoT, social media and mobile devices have led to a seemingly endless flow of digital data that are mostly unstructured and include, among others, human language in written form, such as blogs, posts, reviews, comments, or tweets; speech, such as audio in user-generated content, and images that portray objects or people. In a web form, for example, website visitors may be asked to provide their contact information or give feedback on a product or service by choosing an answer option from pre-determined answer categories (structured data), but also be presented with a comment box in which they can provide additional feedback or questions (unstructured data).

Processes

Artificial intelligence technologies first need to format and standardize unstructured data. These pre-processing activities transform unstructured data into structured data which can then be manipulated in AI's main processes (building block 4) (O'Leary, 2013).

AI Building Block 3: Pre-Processes

Pre-processing of unstructured data in their various forms includes data cleaning, normalization, transformation, feature extraction and selection, with the goal that the remaining data can be processed in value-creating ways.

<u>Natural Language Understanding</u>

Artificial intelligence uses natural language understanding (NLU) to assign meaning to the vast and complicated human language in spoken and written form. Human language comes to life through text (written language) and acoustic signals (spoken language). Before AI can make sense of spoken language, speech first needs to be transcribed into text; this step is typically referred to as speech recognition. Although speech recognition and voice recognition are often used synonymously, the former is concerned with detecting the words that are spoken, while the latter identifies the speaker personally. Speech recognition allows AI to recognize the words that were said, but not what the words mean. This sense-making takes place as part of natural language understanding.

Assigning meaning to written text, i.e., creating a semantic representation of the text, is the most important task in NLU. It is also a challenging task given the ambiguity inherent in natural language resulting from contextual circumstances, linguistic styles or dialog history. For example, artificial intelligence technologies need to separate the meaning of homonyms - words with the same spelling and pronunciation, but different meanings (e.g., to book a criminal vs. to book a hotel room), homophones - words that share the same pronunciation, regardless of how they are spelled (e.g., to, too, two) and homographs - words that share the same spelling, regardless of how they are pronounced (e.g., to tear up vs. to tear down). Adding to this complexity of assigning meaning are spelling errors, jargon, slang or dialect. Thus, a key task in natural language understanding involves analyzing the syntax (i.e., the structure of sentences), semantics (i.e., the relationship between words, phrases and symbols) and pragmatics (i.e., the context in which words or phrases are used of natural language) (Gill, 2017). Early applications of NLU were based on hand-written rules; today's applications rely on machine learning (explained in AI building block 4 below) to extract meaning from text.

While several techniques exist, most NLU applications use a lexicon (a vocabulary) and a set of grammar rules coded into its procedures. These applications then use statistical models and machine learning to apply these rules and determine the most likely meaning of what was said.

The applications of NLU today are immense, and include, among others, automatic text summarization, personality insights, sentiment analysis, topic extraction, named entity recognition, i.e., classifying named entities in text into pre-defined categories, parts-of-speech tagging, relationship extraction, or stemming, i.e., reducing inflected words like fishing and fisher to their word stem fish. As an illustration, the start-up firm Klue offers AI-services using natural language processing and machine learning to curate competitive intelligence from written text in 3.5 million external web sources, processing these data to extract insights for B2B personal selling and sales management. Klue's website promises to provide "a lens for enterprises into their competitor's world, continuously updating and connecting dots to help them win more business." (Klue, 2017). This up-to-date information can better enable sales professionals to answer clients' questions and deposition competitors, in addition to offering valuable insight of what competitors are up to.

Computer Vision

Computer vision is the transformation of visual images into internal representations of the world so that these representations can interface with other building blocks in AI. The degree of sophistication in computer vision varies widely, from recognizing edges or texture to boundaries, surfaces, volumes to the classification of objects, scenes or events (Forsyth & Ponce, 2011). For example, retail technology company Cloverleaf uses AI-enabled computer vision to measure shopper sentiment via store shelves and identify improved pricing or promotion tactics, often in real-time. While easy for humans, visual processing is a highly challenging task for computers, and thereby poses a bottleneck for AI, which need to work from the resulting output.

Computer vision is strongly linked to the field of machine learning explained in the following section, which provides the algorithmic backend to recognize patterns in and extract meaning from pixels. eBay, for instance, is rolling out a feature that allows users to identify an item found on any website – a blog post, or Pinterest, and find similar items on the digital marketplace site by sharing the URL with eBay. Users will also be able to zoom in on specific items within a photo and search for those. While early computer vision systems worked on hand-crafted, human-designed features, today's object classification systems rival human recognition rates.

AI Building Block 4: Main Processes

One of the key processes of intelligence is the ability to apply logic to solve problems and learn. Learning is the process of acquiring new or modifying existing knowledge to better achieve desired outcomes. In AI, building block 4 is primarily concerned with three main processes of intelligent behavior: Problem solving, reasoning and machine learning, with machine learning utilizing the two former processes to make machines smarter.

Problem Solving

Problem solving involves choosing the best solution from a range of alternatives for reaching a goal. Just like with humans, two fundamentally different problem-solving processes exist for AI. In divergent problem solving, artificial intelligence applications generate and evaluate alternative solutions for a given problem. The importance here is that there is no single best solution – a host of alternatives can be equally valuable. Convergent problem solving, on the other hand, is concerned with narrowing down alternatives to find a single-best or even correct answer to a problem. For this, the brute force that AI can employ to deal with big data is particularly helpful.

However, this does not mean that AI problem solving always explores all options to arrive at the optimal solution. Instead, AI often relies on heuristics to reach outcomes that are sufficient for the immediate problem at hand (Tecuci, 2012). For example, when IBM's Watson defeated the human contestants in the TV game show Jeopardy!, Watson determined a list of answers along with a weighting for each answer reflecting its likelihood (or confidence) of being correct. It then used the ranked list to decide whether to answer the question or not and the amount of money to bet. In either case, the divergent or convergent problem solutions are stored (discussed in building block 5 – knowledge base) and existing knowledge is updated (discussed in the below section machine learning).

Reasoning

Reasoning refers to applying logic to generate conclusions from available data. Put differently, AI considers the input to develop reasoned conclusions. It is important to note that there is a fundamental difference between traditional reasoning machines, e.g., data automation systems whose reasoning processes calculate inventory levels or process credit card payments, and AI technologies that provide capabilities for reasoning under uncertainty. Consequently, AI technologies are also thought of as inference engines. They apply rules or laws to the data available to deduce information (Wilson & Keil, 2001).

While problem solving was about finding solutions for problems, reasoning is concerned with the type of logic underlying these processes. Here, too, two main kinds of reasoning exist. Deductive reasoning, also known as top-down reasoning, formal logic, or the scientific method, combines premises, i.e., logical statements that are believed to be true to obtain new conclusions. Accordingly, if the premises are true, so is the conclusion. Theories are tested, and new knowledge is deduced from previous knowledge. For example, IBM Watson Health was fed a large training data set of proteins and used deductive reasoning to identify proteins associated with cardiovascular disease.

On the other hand, inductive reasoning, also known as bottom-up reasoning, does not use rules but instead attempts to generate general hypotheses from specific observations.

The ultimate goal of the AI technology is to detect patterns and develop rules that would not only be conclusive for the data at hand, but that can also be applied to future problems or situations. AI applications, for instance, are used to analyze business-internal data to identify potential future regulatory obligations for the business.

Machine Learning

If the premise of AI is to develop machines that act intelligently, then they need to be able to learn from past attempts. *Machine learning (ML) encompasses techniques that enables computers to learn from* *experience, i.e., progressively improve their performance, without an explicit, pre-defined set of rules that are stored in memory.*

Classic supervised machine learning relied on human decision making to define input features and pre-program specific behavior based on which AI learned. It soon became clear that successful systems would need to learn from experience and derive insight from large amounts of data – without being explicitly programmed.

Advanced versions of machine learning target this question, developing algorithms and statistical methods that are capable to extract (oftentimes implicit) knowledge from data. The advent of deep learning, new GPU (Graphics Processing Units) technology and vast amounts of data now allows algorithms to automatically learn complex features from the data to optimally perform the task that they are trained on. This renders machine learning the most important element of today's AI technologies.

The space of learning algorithms is vast and can be separated into supervised methods (i.e., methods that learn from data for which target output is known), unsupervised methods, and reinforcement learning. Supervised learning methods include computer vision applications, such as object- or speech-recognition, where training data are provided together with correct labels. Unsupervised learning methods aim at finding structure in high-dimensional data to make it more accessible (e.g. clustering, dimensionality reduction). Reinforcement learning tries to teach agents to learn intelligent behavior from their own past experience. In other words, AI learns from various sources, not only from the structured and unstructured input data but also from their own processes. To achieve this, machine learning extends content stored in the knowledge base with new concepts or facts and refines its problem solving and reasoning processes. Thus, machine learning enhances the competence of AI to solve a wider range of problems or increases the accuracy with which re-occurring tasks are solved. This can imply efficiency gains, too, in terms of memory consumption or time spent on task.

No up-to-date AI technology exists that does not use machine learning as a key mechanism to dynamically alter its behavior in an ever-changing environment. As mentioned above, its ability to learn without being explicitly programmed means that it can make data-driven decisions or predictions by recognizing patterns within large data sets, even across various data sources. For instance, Source

Media, a business-to-business media company, uses natural language understanding and machine learning to develop a highly-tailored content strategy to nurture and qualify leads. Using structured and unstructured data from third party providers, its own marketing platforms, and internal sources, Source Media creates prospect profiles and segments them based on users' needs and intents. Employing machine learning, the digital media company delivers highly tailored communications, such as personalized website content, white paper downloads or emails, to nurture and qualify leads ("Lytics | Source Media," n.d.).

Artificial neural networks (ANNs) are one of the tools used in machine learning. Inspired loosely by the human brain, ANNs consist of a sequence of computational stages, also known as network layers, each of which performs comparably simple calculations on its respective input and passes the results of the computations on to the next layer, deeper in the network. Although each computation is mathematically simple, the network as a whole has large computational power due to the cascaded setup, deriving complex mappings from a sequence of simple nonlinear computations (Knight, 2017).

As an example, the computational units in the first layer of a network that performs visual object categorization may receive their input from the pixels of an image and test for the existence of simple oriented lines. The next layer then performs its calculations not on the basis of pixels, but on the level of oriented lines, and thereby detects more complex shapes (curves, crosses, etc.). Like this, units deeper in the network become sensitive to increasingly more complex shapes, resulting in units that are best described as conceptual. For instance, units can be activated upon the presence of a dog, irrespective of breed or viewing angle. The output layer of the network then directly corresponds to the probability that the image contains a given category.

Due to ever increasing data availability and computational power of GPUs, today, there exist increasingly complex artificial neural networks that include millions of parameters. The term "deep learning" or "deep neural networks" describes this new and powerful breed of ANNs (Yao, 2017). While above example describes a visual network performing an object categorization task, networks can learn arbitrary input-output relations. For instance, the input can be pixels, as described above, but also sound-waves (e.g., from a video), temperature scores (e.g., from a sensor), laser-scans (e.g., from medical diagnostics), clicks (e.g., from a user navigating a webpage), and many more - the possibilities are endless. The output can also be diverse, ranging from category labels to speech or robot movements (as described in building block 6). ANN and deep learning algorithms have a variety of marketing applications today, including customer segmentation, predictive lead scoring, ad re-targeting, or dynamic pricing models.

To recap, deep learning is a sub-field of machine learning. Machine learning uses algorithms to parse data, learn from it and make decisions based on what it has learned without human intervention. Deep learning structures algorithms in network layers to create an artificial neural network that can learn and make intelligent decision on its own.

Storage

In intelligent behavior, the fact that experiences influence subsequent behavior is only possible through memory, which stores past data, information or knowledge for future access. AI technology is highly dependent on efficient storage and retrieval of large volumes of data – both in real-time and in data repositories – to solve problems, reason and learn from experience, which leads us to building block 5.

AI Building Block 5: Knowledge Base

A knowledge base stores digital representations of aspects of the real world in which these representations operate, for later access. In the 1970s, such storage places were hierarchical or relational databases that contained rows and rows of structured data. Much like today's AI technologies, they were repositories that allowed the en- and decoding, storing, and retrieval of information from past computations. In the AI context, however, these representations can be structured data or data from pre-processing, but also information generated by the AI system itself, about relationships between objects or events, rules, or actions (Hayes-Roth *et al.*, 1983) for three main AI processes: problem solving, machine learning and reasoning. Finally, knowledge obtained via deep learning is also stored. This form of storage is highly implicit, i.e., the stored computations from a single network layer are impossible to interpret without the context of all others. Deep neural networks can therefore be seen as implicit knowledgebases.

Outputs

Structured and unstructured data, AI building blocks 1 and 2, encompassed accepting sensory input from the environment. Building block 3, i.e., pre-processing (natural language understanding and computer vision) and building block 4, main processing (problem solving, reasoning and machine learning) transformed these inputs in value-creating ways, while the knowledge base (building block 5) stored the resulting information for future purposes. The final building block discussed here entails AI's post-processing interface with its environment. In other words, it refers to what happens in the real world after AI generated its results. In general terms, these outputs can inform human decision making or become inputs into other information systems that then act on the internal or external environment of the business.

AI Building Block 6: Information

Information results from data being placed into a formative context so that meaning emerges. This information resulting from AI can then be used to support human decision making. For instance, digital marketing companies employ AI to improve search engine optimization, mapping content to user profiles and models of what Google looks for in a particular topic. This is similar to how traditional Search Engine Optimization (SEO) keyword search works but expands keywords into semantic topics, thus considering many more topics at a more sophisticated depth than humans.

Likewise, sentiment analyses, such as “emotion AI”, can help marketing managers determine and quantify the attitudes and affective states of customers, information from which educated marketing decisions can be made. For example, marketing agencies and media companies are employing webcams, computer vision and machine learning to determine customers' emotional responses to advertising. The resulting knowledge enables marketers to optimize their media content to the right audiences (e.g., in pre-testing ads) or when to stop showing a specific advertisement. In addition to AI-generated information used in human decision-making, AI-generated information is also used for non-human tasks in a variety of business applications.

Natural Language Generation (NLG)

While natural language understanding (NLU) focuses on identifying the meaning of written text, Natural Language Generation (NLG) performs the complimentary task: *Natural Language Generation (or text generation), produces written narratives in conversational language as output*. Natural language processing (NLP) is the umbrella term that describes an AI's ability to understand and identify the meaning of human language (NLU), decide on an appropriate action and create a response delivered in language back to the human (NLG). By using NLG, organizations can turn large datasets or other internal assets into reports and business intelligence insights, thus bringing a new level of understanding to employee and customer relationships. In addition to internal uses, NLG can also bring economies of scale through applications outside of the organization, for instance by using AI to generate content, for example in advertising or journalism.

The written narratives created through NLG can also take the form of an auditory response delivered back to humans; this is referred to as speech generation. For instance, firms are increasingly using chatbots for "conversational commerce", including marketing, customer relationship management, and post-purchase customer support. A sophisticated AI-empowered speech generator can handle hard-to-pronounce words, as well as alter its pronunciation based on punctuation. For example, capitalized words are emphasized, as a human speaker would when indicating that a specific word is particularly important.

Furthermore, AI applications just recently managed to accurately mimic an individual's voice after learning which sounds go with text as well as learning about the idiosyncrasies of how one talks. Finally, the latest generation of Google Assistant is capable of calling businesses on behalf the phone's owner, engage in two-way conversations and make appointments using sophisticated, deep learning based, speech recognition, reasoning, and speech generation. Equipped with machine translation, the tool will ultimately be able to understand spoken sentences in one language, translate the content and output it in a different language.

Image Generation
Image generation is the reverse of image recognition: when the AI system is fed an image description, even with missing data, it can create complete images as output. Still in its infancy, this element can complete images in which, for example, the background is missing, can alter a photograph to render it in the style of a famous artist or even create completely novel headshots of non-real people. Also, intelligent computers can now generate images from text descriptions. These drawing bots can deliver significant value to business functions relying heavily on visual imagery. Image generation can improve photographers' image editing process and deliver great benefits to graphics companies with a continuous need for new stock for use in advertising. In addition, architectural renderings or animated movies generated from a written script could be valuable applications of AI-powered image generation.

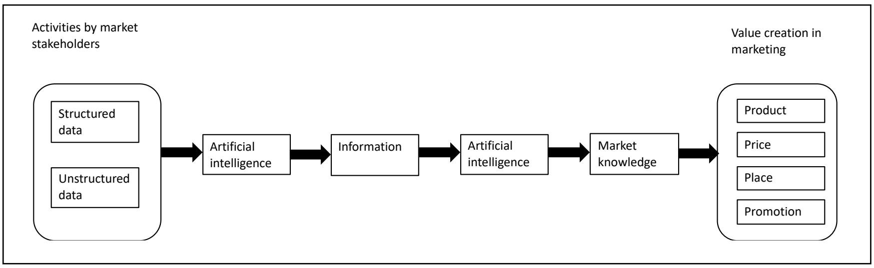
Robotics
While natural language and image generation are outputs that digitally interact with an AI technology's environment, robotics refers to the use of information in machines that physically interact with and alter their environment. Intelligent machines navigate and move through a given physical environment, an application particularly useful in environments where work by humans would be too expensive, too dangerous or sheer impossible, such as disaster relief. Recent advancements in the field of robotics have made robots better at picking up items in warehouses and displaying fluid, humanlike movement and flexibility.

Another application are intelligent conversation agents, such as chatbots. The use of chatbots ranges from engaging in simple conversations with customers, for example, by responding to frequently asked questions or holding more complex dialogues, such as booking appointments on behalf of clients. B2B software company Hubspot, for example, employs a chatbot to generate leads and keep its site visitors engaged. The chatbot is used to capture leads and provides users with more information about its software, in addition to asking the user questions that helps Hubspot qualify visitors either as prospects or current customers. The virtual agent can also re-direct the conversation to a live employee at any time.

How artificial intelligence contributes to the creation of market knowledge: A conceptual framework

Artificial intelligence, as information technologies that act intelligently, can be used in a combination of any or all of the aforementioned building blocks to help B2B marketers create knowledge for a host of marketing decisions. Indeed, at the heart of the argument in this study lies the idea that the inputs-processes-outputs and the use of different AI building blocks within these can help B2B marketers transform data into information and ultimately different types of market knowledge. Market knowledge, defined as knowledge about customers, competitors and other, external market stakeholders (Deshpandé, 2001; Kohli & Jaworski, 1990) enables marketers to effectively tailor their offerings to the actual, rather than assumed characteristics of a market, and has been positively related to enhanced value creation in marketing. The following section hypothesizes how AI enables the creation of market knowledge from big data, which is summarized in the framework in Figure 2.

Figure 2: Creating market knowledge from big data using artificial intelligence



Customers, competitors and other, external market stakeholders create a constant stream of data in structured and unstructured form. Customers, i.e., current and potential buyers and consumers, search for, evaluate, purchase and use offerings. All of these activities create data from which marketers can create valuable knowledge about customers at all stages of the marketing and sales process with the help of AI. AI is able to use structured and unstructured data inputs, such as a recency, size, frequency and the type of past purchases, current web browsing behavior, psychographic and demographic characteristics and interactions with the firm to create a comprehensive profile about current buyers. Using machine learning, these profiles can then be applied to improve customer relationship efforts, and for prospecting of future customers.

In addition, AI enables knowledge about consumers in a number of ways. The explosion of social media use and of IoT has led to an influx of big data that AI can process more effectively and efficiently than humans ever could. For example, AI can analyze vast data sets of written and non-written user-generated content on social media platforms which can reveal insights to B2B marketers about user needs, preferences, attitudes and behaviours (Martínez *et al.*, 2016). The AI application IBM Watson for example, has the capabilities to identify sentiment, emotions, values, and attitudes expressed in a piece of text (Biondi *et al.*, 2017; IBM, 2018). These psychographic characteristics can be a valuable source of insight for B2B marketers for innovation and new product development efforts. In addition, AI can be used to identify themes and patterns in users' posts about their use of a product, which can reveal information about the user experience and point to areas to enhance this experience. Further, the AI-enabled knowledge about users may point to insights of how users creatively alter products and services (Wilson, 2016) which in turn can be a valuable resource for product development and innovation efforts.

The search for, evaluation of and purchase of a product by customers is influenced by the competitors' actions. For example, buyers are using social media to compare products, to research pricing of various sellers or to evaluate post-buying support (Itani *et al.*, 2017). Thus, knowledge about competitors' actions, their strategy, new product, or marketing initiatives is valuable to a focal firm as these actions may in turn impact customers' preferences and behaviours (Calof & Wright, 2008; Narver & Slater, 1990; Rakthin *et al.*, 2016).

Artificial intelligence can support the creation of competitor knowledge by analyzing the vast volume of data that is publicly accessible, for instance on competitors' websites or social media platforms. Using the natural language understanding and computer vision building blocks, AI can analyze text, video and voice data, for example in competitors' videos, thus creating valuable information about competitors' new product releases or pricing changes. In addition, using natural language understanding and machine learning, AI can identify keywords or themes from competitors' news releases, social media profiles and other unstructured data which may provide valuable information about a competitor's strategy. This information can inform a B2B firm's own positioning strategy or help deposition competitors during the sales process.

Moreover, AI can support the creation of other, external market knowledge, i.e., knowledge about external market forces and stakeholders, such as legislators, the public or media, as these external forces may influence customer preferences and behaviours (Kohli & Jaworski, 1990). AI enables external the creation of market knowledge, for example by analyzing the vast amount of online content published by the general public on social media, blogs or third-party news platforms, to name a few. For example, natural language understanding, computer vision and machine learning building blocks are increasingly used to analyze and identify fake news (Berthon & Pitt, 2018; Horne & Adali, 2017) or deepfakes, defined as fake content that is near impossible for a human to discern (Kietzmann *et al.*, 2019).

In summary, the above discussion suggests that AI contributes to the creation of market knowledge through enabling enhanced information quality and quantity from big data. The discussion suggests that the contribution by AI to market knowledge is by assigning meaning to data, e.g., by identifying patterns or relationships. This transforms data into information. In addition, through AI's machine learning and its knowledge base, information is combined with other information and knowledge and in a specific context, thus resulting in the creation of (new) market knowledge. In summary, the above discussion suggests that AI impacts the creation of market knowledge through enabling enhanced information quality and quantity from big data, and through applying information in a specific business context, combining it with other information and data so that knowledge emerges (see Figure 2).

A number of future research avenues emerge from the above discussion. For example, the above discussion suggests that AI may replace or augment tasks that were previously heavily relying on humans, such as creating customer profiles or prospecting. Thus, a fruitful area for future research is to investigate if and how this impacts the role of marketing and sales professionals. For instance, which of the traditional human tasks in marketing and sales are conducive to being performed by AI and to what degree? In addition, investigating how AI changes the value creation process for customers may be a fertile ground for future studies. For example, how can AI facilitate creating, organizing and applying customer knowledge, competitor knowledge and other, external market knowledge at each stage of the marketing and sales process? Furthermore, future research may investigate the role of environmental characteristics in creating market knowledge from big data. For example, how AI can facilitate external market knowledge, when the external environment undergoes rapid and unforeseen change?

Conclusion

This study started off by arguing that, in this time of enormous transformations fueled by digitalization, information and communication technology, recent advances in artificial intelligence will have significant implications for businesses and B2B marketing specifically. The fundamental impact that artificial intelligence will bring about will be on how AI enables the transformation of vast amounts of data into information and ultimately knowledge. The trouble is, as it is with many emerging technologies, that B2B managers eager to adopt these new technologies are unclear about how they function and what their potential impacts with respect to knowledge management strategies and tactics are.

Against this backdrop, this study explains to marketing managers and executives in B2B organizations the foundational components of AI and their interrelationships. Specifically, it introduces a framework consisting of six artificial intelligence building blocks and describes the interrelationships of these building blocks, along with current use cases to illustrate the implications of each building block for B2B marketing.

In addition, this study provides a structured discussion of the implications of AI for market knowledge in B2B marketing. AI can be used in a combination of any or all of the building blocks to help B2B marketers to transform data into information and ultimately different types of knowledge: customer knowledge, competitor knowledge, other, external market knowledge. These activities promise to help B2B firms become more market oriented, specifically by enabling firms to create knowledge about their customers, competitors and other, external market forces. The study introduces a conceptual framework to explicate the role of AI in creating market knowledge from big data. In addition, this study highlights avenues for future research with respect to each of these types of knowledge.

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