**Harnessing artificial intelligence in B2B marketing:
A conceptual framework and managerial guidelines**

Paper type: Work-in-progress

Introduction

Artificial intelligence (AI) is considered the most important *general-purpose technology* of our era (Brynjolfsson & McAfee, 2017). Similar to previous general-purpose innovations, such as the steam engine, electricity and Internet, AI has potential to generate reams of other innovations that have potential for creating competitive advantages and transforming entire industries. According to McKinsey, the early adopters of AI are estimated to share a global profit pool of $1 trillion by 2030 (Bughin, 2018). The promise of AI is fundamentally based on its ability to free employees from repetitive tasks to more productive work and to enhance humans' cognitive capabilities (Wilson & Daugherty, 2018). In particular, AI helps firms in exploiting data for making predictions that can be used for creating more intelligent systems and making better business decisions (Agrawal, Gans, & Goldfarb, 2017; Davenport & Ronanki, 2018).

Yet, despite the massively lucrative opportunities, only a few frontrunning companies have been able to transform their businesses to take a full advantage of AI (Bughin, 2018). There is a huge gap between firms' AI interest and execution. According to a worldwide survey study by Ransbotham, Kiron, Gerbert, and Reeves (2017), 84% of executives believe that AI will allow their firms to obtain or sustain competitive advantage. In contrast, only 23% of the respondents had incorporated AI in some offerings or processes. Thus, about 60% of the executives are excited about the opportunities of AI but have not managed to adopt AI applications. Moreover, those firms that have adopted AI applications are struggling to extract meaningful business benefits from their investments (Davenport & Mahidhar, 2018). To conclude, while many managers are enthusiastic about the technological opportunities, they fail to understand how to unlock the full potential of AI (Brynjolfsson & McAfee, 2017; Ross, 2018).

While the current B2B marketing literature on AI is gradually emerging, it remains in a premature stage and offers only limited conceptual understanding and managerial guidance (Martínez-López & Casillas, 2013). For example, most AI-studies focus on well-known AI-powered platforms and systems such as IBM Watson but fail to provide managerially grounded conceptual frameworks that would explain how firms can harness AI, or leverage AI in different business operations.

Consequently, *the purpose of this study is to explore the valuable use cases of AI in the context of B2B marketing and identify the antecedents of harnessing AI in ways that create business benefits.* We do this by reviewing the literature on the opportunities and challenges of AI usage and applying them for the B2B marketing context. This is a research in progress and the current manuscript is on the conceptual level. Our long-term plan is to draw empirical insights from a theoretically sampled multiple case study (Eisenhardt & Graebner, 2007) centered on B2B firms who are already using AI in their business operations.

CONCEPTUAL BACKGROUND

Advances of artificial intelligence and B2B marketing use cases

The term AI dates back to the 1950s and ever since, it has been associated with futuristic claims and promises of tasks that machines will be able to perform (Brynjolfsson & McAfee, 2017). Too often, the claims have been influenced by science fiction or their timeline has been too optimistic. There is a popular saying that AI refers to cool things that computers can't do (until they do). Therefore, it is no wonder that the term AI remains elusive to many people. According to Oxford Dictionary (2019), AI refers to "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages." Merriam-Webster (2019) offers two alternative definitions and considers AI as "a branch of computer science dealing with the simulation of intelligent behavior in computers" and "the capability of a machine to imitate intelligent human behavior." Common for these definitions is that they are tautological, as they do not define what is meant by intelligence; artificial intelligence is defined as computer-aided or "unnatural" intelligence. In conclusion, AI is a mysterious term but it practically refers to the recent or emerging advances of computer science.

Recent advances of AI have occurred in the field of machine learning (ML), which refers to the science of getting computers act without being explicitly programmed (Lee, 1995). Thus, the promise of ML is that the machines are no longer limited to humans' programming abilities. Instead, the machines can learn complex patterns from data and create models that humans are unable to perceive (Syam & Sharma, 2018). Moreover, even if we can perceive a complex pattern, we may not be able to explicitly explain it or code it to machines. This phenomenon is known as Polanyi's paradox (Brynjolfsson & McAfee, 2017). As an example, most of us know what a strawberry looks like, but we cannot fully transfer the vision of a strawberry to another person who has never seen one by explaining its looks. Because we cannot fully explain the looks of a strawberry, we cannot create a code that would teach a machine to recognize an image of a strawberry. However, this can be accomplished via ML by showing a large number of example images of strawberries to the machine.

ML may create value for businesses in three areas: 1) automation and optimization, 2) insight generation, and 3) perception (Figure 1). First, the automation of routine, standardized and repeatable activities via ML is the most prevalent area of use cases across the industries (Davenport & Ronanki, 2018). It relates to the field of programmatic marketing automation where machines automate the tasks based on rules and triggers designed by the users (Heimbach, Kostyra, & Hinz, 2015; Järvinen & Taiminen, 2016). The difference with programmatic marketing automation and marketing automation via ML is that programmatic marketing automation is just as intelligent as its users. Thus, while programmatic marketing automation is very labor-intensive in terms of designing, analyzing and optimizing the rules and triggers, ML is able to learn independently from data, make changes to the rules and triggers, and thus optimize the process. This may lead to much higher efficiency as it decreases the need for human input and releases employees for other valuable activities. Moreover, the ability of ML to predict complex patterns may improve the outcomes of automation.

In the field of B2B marketing, the automation and optimization via ML fits for a variety of repetitive and clearly defined tasks and processes that the firm encounters. The prerequisite is that the firm has a training data that can be used for teaching the machine to automate decision making. For example, a B2B marketer could use ML for classifying the sales leads into high-quality and low-quality leads to help sales agents to focus on the most likely buyers. In order to make this happen, the firm needs to have data on previous sales leads (e.g., firm size, industry, title, transaction history and behavior on the website) and the outcomes of contacting them (i.e., deal or no deal). As the data accumulates, the ML algorithm will continuously improve its prediction of which sales leads the firm should focus their efforts. Depending on what types of data the company collects, a similar approach can be used for e.g., personalizing and targeting decisions (Davenport & Mahidhar, 2018; Huang & Rust, 2017) , product pricing (Martínez-López & Casillas, 2013) and optimizing logistics routes. Notably, the automation and optimization via ML lead to the incremental optimization of existing tasks and processes. The firm becomes more efficient what it currently does, but this approach may not be helpful for transforming the current practices or inventing something totally new. Incremental optimization does not create sustainable competitive advantage, because when others find the same efficiencies, only the baseline shifts (Ransbotham et al., 2017).

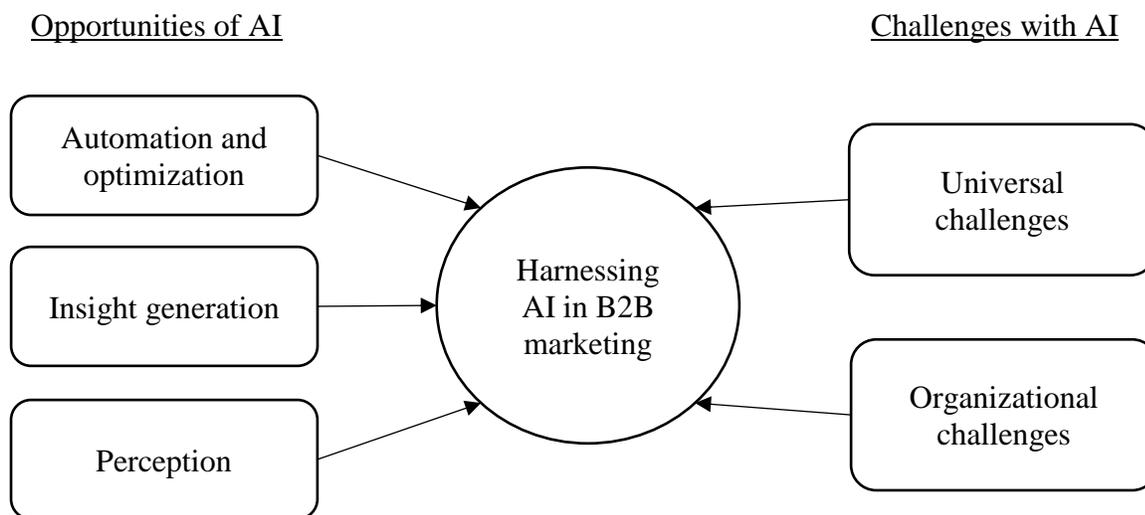Opportunities of AI   Challenges with AI

Figure 1. The opportunities and challenges of AI in B2B marketing

The second area of ML relates to insights generation that complements the incremental optimization by identifying new patterns from vast volumes of data (Davenport & Ronanki, 2018). In this learning mode, the machine is not trained to optimize a specific task but is fed with 'big data', and the machine uncovers patterns from it that may be too complex to be identified by humans (Huang & Rust, 2017). This is a promising ML method in B2B marketing for e.g., gaining new market and customer insights. For example, the machine may find new patterns in customer or competitor behavior, business networks or price movements in the markets. The insights generation brings best results when the firm has access to external data or combines internal data with external data, because the transformative movements in the industry arguably occur in the external environment (Kiron, Prentice, & Ferguson, 2014). Besides the obvious problem of data access, another significant challenge is that the large datasets tend to produce spurious correlations,

and therefore, the role of human judgment becomes extremely important before making hasty business decisions (Agrawal et al., 2017; Chai & Shih, 2017).

Finally, the third area of ML is perception. The perception refers to the ability of machines to recognize voice, images and to process natural language (Brynjolfsson & McAfee, 2017). In a way, the machines have been provided with human-like senses that radically broaden the scope of use cases with machines. Technically, the perception via ML works similarly to automation and optimization. For example, the machine learns to recognize speech by having a training data that includes audio recordings of people talking and their transcripts. Once the machine has processed thousands of hours of audio and transcript data, it learns to recognize words and sentences from the speech. Digital assistants, autonomous cars and chatbots are some famous examples of ML perception. The range of use cases in B2B marketing is very broad and only business imagination creates the limits. However, innovative B2B marketers may use ML perception for augmenting their existing products with new features, coming up with new offerings, or changing their business models as a whole.

Potential challenges of artificial intelligence

Assessing the opportunities of AI in marketing must be considered in the light of some notable challenges. Some of them are organizational in nature that can be solved with proper managerial actions. Others are universal and refer to our inability to understand and model marketing and other social phenomena. In the following, we discuss each category of challenges in turn and discuss their implications for B2B marketing.

The most elementary organizational challenge relates to the volume, variety and quality of data that the organization possesses with regard to the intended use case. The organizations who were inspired by the 'big data revolution' and started to collect data early on will have an advantageous position in harnessing AI (Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; McAfee & Brynjolfsson, 2012). Just like in big data projects, a related challenge is to build an information technology infrastructure to provide an easy data access to everyone who needs it (Ransbotham et al., 2017). If the data is scattered around the organization in different databases, it becomes difficult to take advantage of it. Another data-related issue relates to the hidden biases in data (Brynjolfsson & McAfee, 2017; Dalenberg, 2018; van Esch, Black, & Ferolie, 2019). For example, if the majority of buyers have been from USA, the training data may lead the machine to ignore sales leads from Europe even though the firm would like to expand to European markets. Since the machines are currently not good at explaining their decisions, these types of biases may remain unnoticed (Chui, Manyika, & Miremadi, 2018; Davenport & Ronanki, 2018). For this reason, human judgment remains a vital element in harnessing AI.

The second organizational challenge is to transform organizational processes and workflows in order to join forces between the machines and humans (Davenport & Ronanki, 2018). Machines are best at computation, prediction, automation and optimization, while they are currently weak at abstract thinking, asking questions, imagining and innovating new things, telling stories and leading other people. At the moment, one of the biggest organizational bottlenecks in the use of AI is finding talented people to design and apply ML algorithms to the selected use cases (Ransbotham et al., 2017). However, once the users of AI become commodity, the role of humans

in B2B marketing will be increasingly related to business imagination (Brynjolfsson & McAfee, 2017). That is, B2B marketers are needed to invent new areas where machines could improve performance (Davenport & Ronanki, 2018). The second role of B2B marketers is to lead the other people and create value for customers via dialogue.

The third organizational challenge relates to the negligible role of the B2B marketing function. According to a recent study, the majority of chief marketing officers are mainly responsible for marketing communications, and the situation is particularly common in the B2B field (Whitler & Morgan, 2017). This limits the marketers' ability to apply AI to many strategic actions, such as designing personalized offerings. The other related challenge is the managerial tendency to the overemphasis of short-term productivity measures (Rust, Ambler, Carpenter, Kumar, & Srivastava, 2004; Stewart, 2009). Although a number of studies show that marketing performance should be assessed multi-dimensionally, the c-suite is primarily evaluating marketing performance in financial terms and pressuring marketers to show the return on marketing investments (Ambler & Roberts, 2008; Morgan, Clark, & Gooner, 2002). Taken together, the situation limits the scope of harnessing AI by the marketing functions and motivates marketers to use AI for promotional actions rather than building brands or improving customer experiences (Horst & Duboff, 2015).

The universal challenges stem from the fact that making accurate predictions with ML algorithms require training data of input and output variables that sufficiently capture the phenomenon that the ML algorithm is used for (Chui et al., 2018). In some use cases, this is relatively easy to accomplish. For example, in image recognition the training data involves masses of images of certain objects (e.g., vehicles) as an input data and their labels as an output data (a car, a truck, a van etc.). With this data, the machine will learn to identify different objects with high accuracy because an extensive training set of images is likely to capture the phenomenon of identifying cars almost in its entirety. The trouble is that many marketing phenomena are associated with much more complex dynamics and a significant amount of missing input and/or output data that inevitably lead to less accurate or even false predictions.

There are various types of marketing phenomena but from the perspectives of market orientation (Kohli & Jaworski, 1990), customer relationship management (Payne & Frow, 2005) or value creation (Sharma, Krishnan, & Grewal, 2001) marketing phenomena essentially deal with two variables: marketing actions and market environment. Even with such a simplistic view, the phenomenon is much more dynamic than image recognition because the variables interact. Market environment (input) influences the firm's marketing actions (output), and each marketing action (input) creates a market response (output) and changes the market environment. This may not be a severe problem as ML is found to be most useful in environments with a high degree of complexity (Agrawal et al., 2017). Syam and Sharma (2018) explain that ML can accommodate highly nonlinear and complex relationships between input and output variables, and therefore, it may help us in understanding complex customer behavior in order to design highly personalized offerings. The statement sounds reasonable, but it is noteworthy that the challenge of applying ML to marketing phenomena is not essentially a matter of complexity but a matter of missing data of complex phenomena. The ML algorithms are accurate at predicting statistical truths, but statistical truths do not equal to the real-world truth in case of incomplete datasets (Brynjolfsson & McAfee, 2017).

While a firm can make a careful account of all its marketing actions, our ability to collect data on market environment is limited. For example, the digitization and advances in analytics have indisputably revolutionized our ability to track a customer's digital footprint and interactions with the company, but a notable portion of customer behavior remains uncovered (Järvinen & Karjaluoto, 2015). Marketing managers have access to a customer's transaction history, responses to certain marketing activities, and navigation paths on the firm's website or mobile application, but few companies have data on how customers behave on other digital properties, such as competitive websites, or how they behave in the physical world. Besides missing behavioral data, the underlying cognitive and emotional motivations for behaving in a certain way remain largely uncovered. In such a setting, predictions are not likely to be very accurate.

The failure of predicting marketing phenomena is best illustrated by taking a critical look at successful ML-powered marketing applications. For example, Amazon has one of the most extensive database of customer behavior and its recommendation engine is often publicly celebrated due to its ability to predict the goods that customers are likely to buy. However, Amazon makes a lot of product recommendations throughout the purchasing journey, and arguably, very few people purchase most of the recommended products. Sure, Amazon is better at predicting consumer preferences than probably any other company in the world, but in many other contexts, Amazon's prediction rate would be a miserable failure. For example, if an autonomous car or a cancer recognition device would predict a correct course of action in less than 50% of the situations, most people would be more cautious at declaring them successful use cases.

The above example illustrates the problems when market environment is treated as an input variable and marketing action as an output variable. When the situation is reversed and marketing action is treated as an input and market response as an output variable, we face a new set of problems. First, it is unclear which market response metric(s) should be used (e.g., aggregate sales or profits, individual purchasing decision, brand equity or customer experience) (Ambler & Roberts, 2008; Stewart, 2009). Second, even if a firm selects one of the metrics it wishes to optimize, it remains difficult to form a causal relationship between a marketing action and the market response, because there are a number of other endogenous (i.e., firm-related) and exogenous (i.e., environmental) variables that affect the market response at the same time (Dekimpe & Hanssens, 1995; McDonald, 2010; Pavlou & Stewart, 2000). ML helps in revealing the complex patterns between these variables and the market response, but only if there is data available on each of them. Unfortunately, this is practically never the case, which leads to less accurate predictions of the market response.

CONCLUSIONS

AI provides enormous opportunities for B2B marketers, and it will revolutionize the tasks and processes that marketers currently execute. At this point, we have explored some of the use cases of AI in the B2B marketing and pointed out potential challenges that the B2B marketers will face in the adoption of AI. In the next stage of this study, we will conduct field interviews with companies in B2B markets who employ AI, and explore the capabilities and strategies firms use to harness AI, and potential business benefits they derive from AI-enhanced processes. We will report the preliminary findings from the field interviews in the conference.

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