Artificial intelligence (AI) and value co-creation in B2B sales: Activities, actors and resources[1]

Abstract

Artificial intelligence (AI) allows business actors to exchange resources, particularly information and knowledge, to strengthen their businesses. These AI-enabled value co-creation processes are playing a substantial role in the business-to-business (B2B) sales context. However, little is known about the mechanisms and the process of value co-creation enabled by AI. On this basis, this study addresses this gap by employing Service-Dominant Logic to understand value co-creation with AI. This study identifies the value co-creation process, and provides an understanding of the actors, activities and resources during the usage of AI to create value in B2B sales. The study also identifies several limitations of AI, such as, value co-creation is heavily dependent on human activities and resources. Lastly, we suggest that managers continue to manage customer expectations when using AI for value co-creation and highlight the necessity of human actors and resources in the value co-creation process.

Keywords:
Artificial Intelligence; Value Co-Creation; Service-Dominant Logic; Competitive Intelligence; Machine Learning; B2B Marketing, B2B Sales, Resources.

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Introduction

The profound transformations brought about by artificial intelligence (AI) announce the beginning of a new era: the fourth industrial revolution (Schwab, 2016). As we enter this new era, AI technologies will enable computers to be actively involved in human decision-making and may even allow computers to make suitable decisions without human involvement (Black and Van Esch, 2020; Paschen *et al.*, 2020; Syam and Sharma, 2018). This shift is currently underway and is having profound impacts on all aspects of B2B marketing (Eitle and Buxmann, 2019; Paschen, Pitt, *et al.*, 2019; Syam and Sharma, 2018), including the nature and process of how service is exchanged in B2B marketing interactions. Today, AI enables economic actors to exchange resources, such as advanced information and knowledge (Paschen *et al.*, 2019; Van Esch *et al.*, 2019) to create value and to improve their respective positions (Lusch, Vargo, & Gustafsson, 2016; Vargo, Maglio, & Akaka, 2008; Vargo & Lusch, 2004). These AI-enabled value co-creation processes are the central phenomenon investigated in this article. Specifically, the research presented in this study investigates the process of co-creating value by means of AI in the context of business-to-business (B2B) sales.

Investigation of AI-enabled value co-creation in the context of B2B sales is important for a number of reasons. Recent academic literature suggests that the B2B sales field will be substantially impacted by AI, and that these impacts will change both the nature of and the process of value creation (Martínez-López and Casillas, 2013; Paschen, Wilson, Ferreira, 2020; Singh *et al.*, 2019; Syam and Sharma, 2018). Yet, despite this impact and the increasing adoption of AI among professional service practitioners (MIT Technology Review Insights, 2018), there currently exists little understanding about the mechanisms and process of value co-creation enabled by information and communications technologies (Breidbach & Maglio, 2016), let alone about those enabled by AI (Black & Van Esch, 2020). As a result, recent works call for research to address this gap (see Duan, Edwards, & Dwivedi, 2019; Martínez-López & Casillas, 2013; Singh *et al.*, 2019; Syam & Sharma, 2018).

In response to this call, the current research explores the process of value co-creation in B2B sales. In this article, we provide an empirical investigation using in-depth interviews of AI-enabled value co-creation processes in the context of the B2B sales. The research question that our study aims to answer is “How do economic actors in B2B sales systems co-create value by means of artificial intelligence?” To answer this question, we build on the argument of Anderson, Challagalla, and MacFarland (1999) and Füller (2010) which suggests that any interaction, including value co-creation, can be understood by investigating the actor(s) (i.e., who?), the activities (i.e., how?) and the resource(s) (i.e., what?) of the interaction. This tri-partite framework has been employed in previous research on value co-creation (Breidbach & Maglio, 2016) and is adopted for the current research using Service-Dominant Logic (SDL) as a lens.

In answering these research questions, this research focuses on a critical task in B2B sales: the generation of competitive intelligence. The importance of competitive intelligence has long been acknowledged in the literature and rests in the influence that competitors can have on customers’ needs and behaviors and on the market in general (Day, 1994; Kohli & Jaworski, 1990; Narver & Slater, 1990). Therefore, collecting and applying intelligence about a competitor’s offerings and strategies is a critical undertaking in B2B sales (Itani, Agnihotri, & Dingus, 2017). The increasing digitization (Syam & Sharma, 2018) and growing use of social media (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011) has resulted in vast volumes of data, termed big data, that can impact the nature and process of competitive intelligence generation in B2B sales (Meire, Ballings, & Van den Poel, 2017). Specifically, big data is so vast in terms of the five V’s (volume, variety, veracity, velocity and value) that traditional information technologies are ill-equipped to analyze and processed these data. Artificial intelligence, on the other hand, has been discussed as one information technology that is capable of extracting information and knowledge from big data (Duan *et al.*, 2019; Paschen *et al.*, 2019).

The remainder of this study is organized as follows: drawing on SDL, this study first provides a discussion of the current literature on value co-creation and artificial intelligence. Next, we describe our research methodology and data analysis. Following this, we present the findings from our empirical study using in-depth interviews. We conclude by discussing the implications for research and practice and by identifying future research opportunities.

Value co-creation and artificial intelligence

Artificial intelligence

The term ‘artificial intelligence’ could be misleading, in that it suggests the possibility that computers display human-like intelligence (Kaplan & Haenlein, 2019; Russell & Norvig, 2016). This is not the case. Instead, AI encompasses information technologies that act rationally based on the information they have (Paschen *et al.*, 2019; Russell & Norvig, 2016; Tecuci, 2012; Van Esch & Black, 2019). Artificial intelligence solves problems to achieve the best outcome or, in the case of uncertainty, the best expected outcome.

Our definition of AI in this study departs from the notion often adopted in the popular media by which AI emulates human intelligence; like other academics, we conceptualize AI as information technology that acts rationally, based on the information available to them, in order to solve problems. It should be noted that the uses of AI in this study fall under the umbrella of ‘narrow’, rather than ‘strong’ AI. Narrow AI describes AI technology that is optimized for a given task. Strong AI, also known as artificial general intelligence, describes AI that is capable of solving any intellectual task, similar to humans. AI in this study encompasses narrow AI technology.

Across applications, any AI technology can be explained using an input-process-output model: AI requires data from its environment (inputs), manipulates such data in value-creating ways (processes), and feeds information (outputs) back to the environment (Paschen *et al.*, 2019).

Inputs

Inputs to AI include structured and unstructured data from a variety of sources. Structured data includes standardized datasets in numerical form (for example, age, zip code, web clicks, or transaction records), or unstructured data, which is qualitative data (for example, text or audio comments, images, or videos). Unstructured data comprise about 80 percent of the world’s data today (Rizkallah, 2017) and are growing 15 times faster than structured data (Nair & Narayanan, 2012).

Processes

Artificial intelligence can process vast amounts of structured data efficiently but is particularly effective and efficient at processing unstructured data. Natural language understanding (NLU) and machine learning (ML) are two important processes of AI technology. NLU - in practice often referred to as natural language processing and abbreviated as NLP - analyzes text and assigns meaning to human language in spoken and written form (Paschen *et al.*, 2019; Syam & Sharma, 2018). Here, NLU considers the syntax (sentence structure), semantics (relationship between words, phrases and symbols) and pragmatics (context in which words or phrases are used of natural language (Gill, 2017).

A second important AI process is ML, which encompasses computational procedures that enable AI to learn itself, i.e., improve its performance, without being explicitly programmed to do so (Russell & Norvig, 2016; Tecuci, 2012). In supervised ML, an AI technology is provided with training data sets that include the inputs and the correct outputs (i.e., correct answers), from which the computer learns the patterns and develops the rules to be applied to future instances of the same problem. In unsupervised ML, on the other hand, AI is using training data that are not labelled with the correct answers, identifying patterns or relationships between the data points. For example, unsupervised learning can be used to identify products that are ordered together. The third type of ML encompasses reinforcement learning in which AI learns from its own experience. It differs from supervised learning in that the correct input/output pairs need not be presented. Instead, the focus is on finding a balance between exploration of uncharted 'data territory' and exploitation of current information based on past experiences (Kaelbling, Littman, & Moore, 1996).

Outputs

The remaining component of AI technologies encompasses outputs, or the information resulting from the above value-creating processes that feed into various business applications (Paschen *et al.*, 2019; Tecuci, 2012). In its basic form, AI produces information; in the context of sales, this information may consist of lists of topics frequently mentioned in news articles about a competitor or an industry. This information may then require further actions by human decision makers, such as an analyst, using AI-generated information about a competitor to create sales battle cards. In addition, some AI technologies act independently of human input. For instance, consider an AI-enabled chatbot responding to consumer inquiries or AI creating ad copy or news reports.

Artificial intelligence and value co-creation

SDL is centered on the premise that service, rather than goods are exchanged between economic actors, i.e., customers and producers (Vargo *et al.*, 2008; Vargo & Lusch, 2004). Service encompasses the application of knowledge and skills, and value is created in the integration of resources during an exchange process between producers and customers (Vargo & Lusch, 2016). Resources are core to the value (co-)creation processes; SDL asserts that value processes are resource integration activities. According to SDL, resources can either be operand or operant resources (Vargo & Lusch, 2004, 2016). Operand resources are often tangible assets, such as financial capital, raw material or equipment, and are often static and finite (Lusch & Nambisan, 2015). Operant resources are resources that act on other resources to produce an effect; they act on other operand and other operant resources rather than being acted upon (Constantin & Lusch, 1994). Operant resources are often intangible and dynamic, such as human skill or knowledge. While operand resources are important, SDL emphasizes the application of operant resources, such as specialized knowledge and skills, for reciprocal benefit creation (Vargo & Lusch, 2004).

In the extant literature, a number of studies investigate technical aspects of AI technologies and value (co-)creation (Bottani, Centobelli, Gallo, Kaviani, Jain, & Murino, 2019; Dubé, Du, Mcrae, Sharma, Jayaraman, & Nie, 2018). Yet, other scholarly work explores value (co-)creation with AI technologies from the perspective of the beneficiary. Čaić, Odekerken-Schröder and Mahr (2018), for instance, study socially assistive robots built on AI for service provisions in elderly care, focusing on AI's value creating and value destruction potential. From their study, the authors identify six roles of socially assistive robots in an elderly person's value network and link these roles to different health-supporting functions in elderly care.

Other authors take a meso-level, (i.e., an organizational-level perspective) to understand value creation and AI. For example, Russo-Spena, Mele, and Marzullo (2019) investigate value innovation enabled by AI, using IBM Watson's cognitive computing application as an illustration. The results suggest that AI prompts new service provisions and enables new interactions between humans and non-humans, resulting in value co-creation opportunities.

In another study, Knote (2019) studies service design criteria for AI-enabled robots in the automobile manufacturing industry, using a customer lens. Kaarteemo & Helkkula (2018) perform a systematic literature review in sixteen top marketing and service journals on the topic of AI and value co-creation. The results provide evidence that most of the reviewed articles (81%) focus on how AI applications support service providers, for instance, in predicting market changes, understanding customer preferences and behaviors, or in performing other cognitive tasks, such as customer feedback analysis or product development decisions. Only 9% of the reviewed articles focus on how AI technologies enable value co-creation between firm and customer through enabling resource integration. The remainder of the articles focuses on general field advancement (6%) or value creation for the beneficiary (3%). Compared with a large number of practical AI applications, the topic of AI and value co-creation remains underexplored. Particularly, the topic of resource integration offers opportunities for further scholarly investigation.

The above discussion highlights the important contributions from existing research towards the goal of developing and enhancing the body of knowledge of value co-creation and AI. However, the above review of the literature also suggests that the topic of co-creation of value, and in particular co-creating value propositions, and AI has not received adequate scholarly attention. While scholarly interest and publications have been growing in the last decade, a majority of studies have focused on studying technical aspects of AI (Russo-Spena *et al.*, 2019), have been conceptual in nature (Huang & Rust, 2018; Syam & Sharma, 2018) or adopted an organizational-level perspective (Kaplan & Haenlein, 2019; Russo-Spena *et al.*, 2019).

Moreover, the above literature review suggests that insufficient scholarly attention has been given to the co-creation of value and how this process is shaped by AI using a micro-level perspective, i.e., from the perspective of the individuals involved. This is important to understand as the core of value creation: according to SDL, economic actors co-create value through exchanging resources. Thus, a research opportunity exists to further understand value co-creation from an individual perspective.

This study responds to this opportunity by adopting a micro-level perspective on the co-creation of value using AI in B2B sales.

Methodology

Our study examines the interactions of humans and AI in B2B sales service systems, specifically exploring actors, resources and activities during value co-creation. Given the exploratory nature of our inquiry, we deemed a qualitative research approach best suited for our investigation. Specifically, we deemed semi-structured interviews an appropriate approach. Interviews enable an in-depth understanding of the construct of interest, and let a researcher follow up on initial responses, asking individuals to clarify or elaborate (Brashear *et al.*, 2012). This flexibility allows deeper understanding of the respondent's answers while still providing structure to organize and understand the data and is appropriate for the exploratory nature of the research conducted in this study (Van Esch and Van Esch, 2013).

Informants

A purposive sample was used for this research. Specifically, the individuals interviewed for this research were employed at a North American start-up company that provides competitive intelligence services via AI information technology built on ML and NLU. The company collects data from publicly available online sources, as well as from internal sources, and then filters and organizes this information for use by clients. Specifically, data is gathered, stored, de-duplicated, and categorized. After this, the information becomes ready for review and further curation by the client's sales professionals (sales staff and sales enablement staff). The clients' professionals work in corporate sales (or corporate sales enablement) of information technology products and services. For further clarity, informants included employees of the start-up company providing AI services to its clients who in turn work in corporate sales of information technology.

The individuals interviewed for this research encompassed employees in a range of roles, including Sales Development Representatives, Account Executives, Customer Success employees, Marketing Coordinators, Head of Marketing, Front End and Back End Technology Developers, and the Chief Technology Officer. The researchers were given access to informants for scheduled interview times by teleconferencing software. Interviews were booked in 30-minute appointment slots.
The researchers utilized the guidelines of Lincoln & Guba (1985) in determining when data collection should be terminated which suggest that data collection should end after at least one of the four conditions are met: (i) that no further data sources are available, (ii) that theoretical saturation has been reached, (iii) that regularities have emerged and a sense of integration has been achieved, or (iv) that collecting new information is beyond the scope of the research question. In the present study, after interviews with 14 employees were complete, conditions (i), (ii) and (iii) were met and data collection was ended. Moreover, our final dataset consisted of interviews with 14 employees (Table 1). Each interview lasted for an average of 31 minutes, with a range of 16 to 41 minutes. The total interview time was approximately 7.25 hours.

Table 1: Overview of informant functions

	Number of interviews		
Functional area	**Senior Management**	**Team member**	**Total**
Marketing	1	2	3
Sales	2	2	4
Customer Success	1	1	2
IT Development (front-end)	2	1	3
IT Development (back-end)	1	1	2
Total	**7**	**7**	**14**

Data collection

The first step of our data collection consisted of developing a draft of interview questions based on the research objectives and extant literature. The researchers sought feedback on this draft from colleagues and used this feedback to make modifications to the interview questions. Subsequently, two interviews were conducted using the updated interview guide. Following these initial interviews, the interview questions were modified taking into account the flow of the conversation and feedback from informants. This led to the creation of a final version of the interview questions that was used to guide the remainder of the data collection. The final semi-structured interview process began with a question about the respondent's role and tenure within the target company, followed by a general question about their definition of AI. After informants had given their initial response to a question, the researcher followed up with clarification questions. The interview questions focused on the benefits of AI in B2B sales, the process of value co-creation, the role of human contributions and AI, the role of human contributions and whether they perceived limitations of AI in B2B sales.

Immediately after an interview, the interviewer wrote a memo that summarized initial impressions of the interview, as well as any aspects of the interview that stood out and how the conversation fit in with previous interviews. The audio-recordings of the interviews were transcribed into MS-Word files using a professional transcription service. One researcher reviewed a sample transcription, compared it word-for-word with the original audio data, and concluded that the MS-Word files represented an accurate representation of the audio files. The interview transcripts and the researcher memos served as the dataset for this study. The data analysis is described in the section that follows.

Data analysis

Data analysis encompassed a thematic analysis approach (Fereday & Muir-Cochrane, 2006) as the appropriate method, as it enables a search for themes by recognizing patterns within the data and facilitates the organization and description of the data in rich detail. Data collection and analysis were conducted simultaneously to allow for flexibility. Throughout this process, the data were analyzed using aspects of grounded theory (Glaser & Strauss, 2017; Strauss & Corbin, 1997).

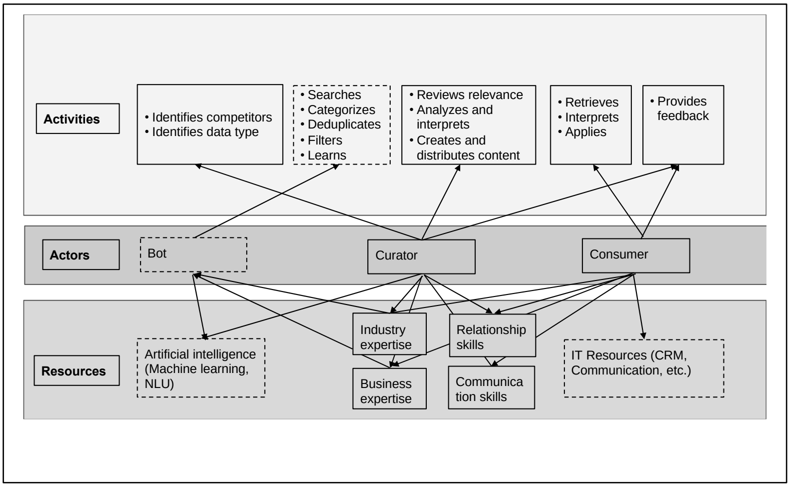
Data analysis followed the phases of thematic analysis as described by Braun and Clarke (2006). Each transcript was systematically reviewed by one researcher and initial, first order codes that were informant centric were developed. The aim then was to generate initial

codes that were subsequently collated into themes; constant comparison of these labels allowed higher-order labels to be extracted.
This iterative process led to the identification of core categories, which were then utilized in the next stage of coding: axial coding (Strauss & Corbin, 1997). In this stage, similarities and differences and the relationships among and between the categories and were sought. Finally, results of the analysis were examined using negative case analysis to enhance the rigor of the investigation. This involved re-examination of each interview after the analysis was completed in order to determine whether the emergent themes were indeed applicable. This process revealed no disconfirming evidence. The final review substantiated that the themes reflected the meanings evident in the dataset as a whole.

Findings and Discussion

The start-up firm provides collection, storing, filtering, and categorization of data and information for clients. The value that the focal firm provides is heavily co-created with clients, as clients are ‘curators’ of the information that is given to them. As ‘curators’, their task is to further condense the information, use their industry knowledge to make sense of it and provide it to their sales teams in easily digestible, timely formats. The sales professionals benefitting from this process are classified as ‘consumers’. They primarily take this information and use it in the selling process to handle customer objections or position own products favorably against competitors. The details of the value co-creation process are described in the following sections. Following earlier research on value co-creation by Breidbach & Maglio (2016), our investigation will focus on the actors, activities, and resources of the interaction as posited earlier by Anderson *et al.* (1999) and Füller (2010). This is summarized in Figure 1.

Figure 1: Value co-creation: Artificial intelligence and human actors



Actors in the value co-creation process

The interviews described three actors in the value co-creation process: these are the ‘bot’, the ‘curators’, and the ‘consumers. The ‘bot’ refers to the data gathering and processing software algorithms including the AI developed by the company and is the non-human actor involved in the value co-creation process (indicated by dotted lines in Figure 1). The ‘curators’ are individuals who provide support (in the form of information management and knowledge creation) to the end users. Specifically, curators are employed by the clients and serve to curate the information gathered and provided by the bot. Finally, the ‘consumers’ are the end users of the information that has passed through the bot and the curators. These individuals are employees who hold sales roles.

Therefore, the flow of activities between these actors is as follows: the ‘bot’ seeks out data that is of interest to clients, generally competitive, industry, or market information. It is collected from a broad range of publicly available sources – from company and news websites, blogs, and social media feeds to court filings, patents and public financial reports, but also from internal sources such as data and information logged in customer relationship management systems. Duplicates are removed and the most relevant data is determined based on prior customer specification and the subsequent ML of the bot.

This relevant data is deposited in a central repository where it is available for a review by client employees called ‘curators’. These curators are generally employees in sales enablement roles, such as competitive intelligence, product management or product marketing roles with extensive industry and other subject matter expertise that they use to make sense of the data they have received. As informant 13 stated: “*…it’s easier for a curator to organize and digest… It doesn’t really become intelligence until somebody says this is what it means, right?”*. They edit, sort and compile data and information into easily digestible, highly relevant and concise content pieces that are then made available to the final actors in this process, the ‘consumers’. Consumers in this context are generally sales professionals who rely on the curated information provided to facilitate their sales efforts – positioning their product and company in an accurate and up-to-date competitive landscape, handling objections, and negotiating terms and pricing.

The ‘bot’ can be classified as an actor in this process due to the ML and NLP capabilities it employs to find, de-duplicate and, in the words of informant 9, ‘*auto-curate a little bit*’ the content that is relevant to the customer. This information is made available to the curators, who apply their existing expertise and knowledge to extract relevant information from this input, therefore ultimately extracting value from the information provided by the service of start-up firm. As informant 11 put it: *“The curators are the creators of the content”*. This succinct quote signals the important role of the clients in creating value: ultimately, it is the knowledge and expertise of a client that enables a wealth of information to be turned into knowledge.

This content produced by the curators is mainly provided directly to the consumers, which are generally employed as part of the sales team of the company customer. The internal label of “consumer” of the resultant information has been picked deliberately, as described by informant 3: *“…we call our sales people consumers, because they're consuming the information. That is an internal .. term.”* The consumer’s role is largely limited to the ‘consumption’ of the information in a narrow sense – retrieving it in easily digestible formats from the central repository provided by the application and using it to create competitive advantage in the course of their sales cycle. The influence of the consumers on the value co-creation process is described as limited, with informant 13 describing the situation as there being *"...not a big feedback loop on it"*.

By exploring the roles of actors, we took the first step towards understanding AI-enabled value co-creation processes. In the next section, we present our findings regarding the practices. Specifically, in what follows we discuss the activities that actors engage in when exchanging resources.

Activities in the value co-creation process

The value creation process begins with collecting data from varied sources. A critical activity is dealing with the sheer volume of data that is available in competitive industries. The value created in this stage is heavily co-created between the bot and the curators and encompasses saving time and effort in data collection. This was brought up by informants 1, 3, 4, 7, 11, 12, 13 and illustrated by informant 11's quote: *If I'm interested in a particular business or industry or whatever it's hard for me as a single human to keep track of everything that's going on in that space.*", while informant 3 noted: *So [the AI service] for the intel collection, so we have a bot, goes out, scans the internet for information on your competitors or on the company's competitors, so really it's helping people save time in their day-to-day workflow. Doing full-blown research takes time and as you know, during research right now, takes a bunch of time. ... So it's going to be a big benefit of choosing [the AI service] and why companies and users decide to go with [the AI service] is because we're helping automate that process*.

The curators identify relevant competitors and type of data required, using their industry and business expertise, as summarized by informant 4's quote. *"During the collection stage, of course, they're placing a lot of their input into what matters, and what's important to them. So a bot can't read minds. It can't go out and pull, obviously, information that you're looking for, if you don't know what you're looking for. We need to know what's important to you ... and what you care about. We work with you in that sense, to figure out what's* *important to you."* The identification of relevant data as an important activity was also mentioned by informants 1, 2, and 12.

The data collection undertaken by the bot becomes progressively more targeted as the algorithm is optimized by ML depending on the curation efforts, as stated by informant 12's quote: *"Instead of a human going through a thousand alerts and kind of categorizing and filtering them through, our AI and machine learning can do that for you."* For example, when a curator marks something as important or unimportant, the bot learns this and adapts its algorithm accordingly. This is a quality that informant 9 sees as central to value creation: *"Improving the quality of the data coming through, ... That's part of the work that we're trying to refine. There's also the deduplication of a lot of bad quality data or redundant data that needs to be filtered out, and also timeliness of data. ... If we find something three days later no one gives a crap, but if you find it the same day or an hour after it happened then we were like the rockstar, right?"* Interestingly, the volume of data that would present an issue for a human is of crucial importance to ML process, as illustrated by informant 1 "*we have bots that go out and look at millions of news sources everyday and pull in all the content that you're gonna care about*" and was also brought up by informants 7, 9, 11, and 13. A lack of volume was seen as prohibiting value, as described by informant 11: *"..., we haven't had enough time or volume of data, I would argue, to accurately train the AI."*

The sentiment that the progressively better targeting, filtering and initial sense-making constitutes an important part of the data collection was widespread among the informants and precedes the presentation of the information to the formal curators, whose contribution to the value creation process is widely accepted as central. As informant 4 described of the curator's role: "*What's valuable are the insights that's derived from the data, that's made in combination with the subject matter expert's knowledge and expertise in the industry. That's why I find curation to be the most important aspect. Without that human element and that subject matter expertise, it's really just raw data that's not that useful*". More succinctly, informant 7 observed: *"It's very possible for there not to be value if a human element is not added."* Also, in acknowledgement of the curator's contributions, informant 13 emphasized how the app is built to work with the curator's existing workflows: *"... they're struggling with spreadsheets ... and more generic multi-purpose tools. And this [app] is something that's really kind of* *custom built for how they think... They can see that it would be something that would get used and make them look good".* This theme was also highlighted by informants 2, 3, 7, 9, 14.

The output of the curation consists of easily interpreted, concise, and company-specific 'battle cards', as well as more elaborate competitor boards and ongoing feeds and digests. With the completion of the various types of output, the data pieces flagged as relevant in this process are fed back into the ML algorithm to improve the pre-qualification of the data that is provided to the curators in the next round of information gathering. In this way, the app becomes what informant 9 referred to as a *"virtuous cycle"*, which is intended to continuously improve the quality and speed of the process.

As described above, the consumers as the final recipient of the information realize the value created in the AI-supported data gathering and curation process, but they have limited opportunities to actively shape this process, which informant 9 discussed: *"The only thing they [the consumers] can really do is provide commentary. They can augment on feed posts, they can comment on a card, they can send in an email through their email client and it gets indexed and printed, ..., but they can't really edit anything in there."*

In reviewing the activities performed throughout the value co-creation process, it becomes apparent that the contributions of human and artificial intelligence are distributed through the different phases commonly identified by the informants. Table 2 shows an overview of the three phases of data collection, curation, and information consumption broadly mapped to the contributions of human and artificial intelligence to value created in each phase. The visual representation depicts the approximate value contribution by the number of the asterisks in each cell. The necessity of extensive utilization of human intelligence becomes apparent in this overview. This was quoted by informant 11: *"...right now the product is more human powered than machine powered."* and *"Ultimately we give the largest weighting to human, if a human says it is relevant then it probably is..."*

Table 2: Value co-creation artificial intelligence and human actors

Value Creation Phase	Value created by Artificial Intelligence	Value created by Human actors
Data Collection	***	*
Curation	*	***
Consumption	*	***

Therefore, the processes undertaken by the three actors lead to value creation in a variety of ways. In creating value, each of these actors requires resources; this is the focus of the following section of this manuscript. Specifically, the following section will show that this distributed value co-creation is also reflected in the allocation and use of resources in the service delivery process.

Resources in the Value Co-creation Process

The resources used in the value co-creation process are distributed between the human actors and AI. The resources for the data collection phase, which is driven by a mix of simple algorithms (such as web crawlers and scraping tools), are largely related to computer processing requirements. As informant 9 stated: *"… if you think about how people used to do things …; if I can read a script that can do it, especially efficiently, I can throw a lot more juice at it. … cost of computing is so low that if I can match what some group of people sitting in a call center somewhere is doing with a few scripts and get that turned around, I can run it at a few cents per hour and save myself a ton of money. … In terms of finding content, we can process much larger volumes of information in a very short span of time and it's literally just a matter of throwing processing power at it, which just costs money. If they can keep the cost down and keep the amount of power up then we can do a lot more than we could normally."*

In addition, other resources at the data collection phase include industry and business expertise by people. First, industry expertise is necessary for the client organization, typically sales enablement employees, to identify which competitor to generate intelligence about and what type of data may be relevant. As stated by informant 4: "*Anyone can copy and paste raw data from the web, and hand it to a sales rep but it's not going to be useful or valuable. What's valuable are the insights that's derived from the data, that's made in combination with the subject matter expert's knowledge and expertise in the industry*." This view also was mentioned by informants 1, 2, and 11.

Second, once data has been collected, sales enablement staff evaluate the relevance of the data, applying their subject matter expertise. This is emphasized by informant 3's quote *"The start of it at the collection point and how they ... the product marketers are the ones that are going to be looking at the material and deciding whether or not our bot and our machine learning component is actually doing its job"*. The importance of subject matter expertise was also mentioned by informants 7, 11, and 13.

Human resources are essential to the curation phase and are largely based on industry experience, technical expertise, and other nuanced or experience driven abilities such as being able to interpret industry or company-specific terminology. As informant 13 stated: *"Plus, one company looks at things entirely different in one industry than another company in another industry would do. So you still need ultimately that subject matter expert to evaluate this information and think about it and know what does this mean for us, for our company, for the people that work here."* Therefore, a central undertaking involves the curators applying their human knowledge appropriately and consistently to achieve maximum effectiveness and efficiency with the AI service. In cases of prolonged periods of neglect, a backlog of information builds up. This backlog makes it difficult to continue extracting the maximum value. At the same time, the human resources (business knowledge, industry expertise) brought by the curators is seen as currently irreplaceable. In the words of informant 11, *"... on one end of the spectrum you have humans that are largely right most of the time. And on the other end of the spectrum you have this machine learning algorithm that is right some of the time"*. Similarly, informant 13 stated that *"... when the stuff is really on the fringes of nuanced human languages, especially when most of the systems at work are based on English dictionaries and patterns.... So* *where the distrust comes in, is in the false negatives or the false positives"*.

The final part of the value co-creation process is distribution to the consumers which involves creating content (battle cards, sales communications, newsletters and others) that is easily understood by and accessible to consumers. One component of this involves utilizing the digital tools that the consumers use anyway. As informant 4 explained: *"They don't have a lot of time to jump through different things, so we place [the app] everywhere that they're already living"*. As a result, the app uses resources on multiple mobile or web-based platforms to ensure easy accessibility for the consumers. As explained by informant 7: *"There are many different access points of how they can get this content going into [the app]: emailing, using Salesforce, using Slack, using our Chrome extension."*

In addition to accessibility, the distribution activities of the content rely heavily on human curators in interpreting the information pulled in by the AI service and translating it into knowledge about competitors: This was consistently brought up by a majority of informants, for example informant 1 noted *"So at the end of the day they're [the curators] the ones creating those battle cards in general terms and creating detailed competitor profiles... they're taking all that content and then moving it into various pieces of content, moving it into battle cards and boards, and organizing it the way that they know, cause these are the subject matter experts at this point."* While informant 2 summarized *"We're [the AI service] bringing in some articles and things for them, but there's still a ton of analysis that has to happen on those, before they create anything that can go out to the Sales team."*

Across all stages, data collection, curation and consumption, AI provides operand and operant resources. As an *operant* resource, AI is acts on data collected from various web sources and customers' internal data sources. Artificial intelligence also acts on human resources, including business and industry knowledge, for example by learning from the feedback provided by curators and consumers. As an operand resource, AI is being acted upon by human input. Human curators, for example review the information collected and organized by AI and curate this information further to provide insights for consumers.

Trust and engagement.
Artificial intelligence brings about many unique benefits, such as informant 10: "*AI enables humans to go further, enables humans to do things that typically exceed human capacity / capabilities*", however, several informants state that there is skepticism and lack of trust towards it. For instance, informant 6: *"Sales people show some resistance to the product – this may be lack of trust"*. Also, informant 7: "*...the main challenges is perhaps skepticism towards AI as a lot of people still don't trust the auto magic button or the automated items that are getting pulled in from any software"*. This suggests that, the lack of trust and skepticism towards the product may cause lower engagement levels in terms of actors, activities and resources. Following this, informant 3: " *...if clients are willing to put the effort in continuously to using this technology properly, the benefits are going to be huge to them but if they put it on the back burner for a little bit, not only are they not getting the benefits, but it could actually become this massive undertaking that's going to be prohibitive in moving forward".* Therefore, before starting to use AI, actors and organisations must understand the value and benefits of AI and how to implement this technology-enabled tool correctly.

Limitations and Suggestions for Future Research

This research answers calls for better understanding of the role of AI in what may very well be a fourth industrial revolution. However, much remains to be understood about the role and use of AI in B2B sales. Future research should continue to explore this area in order to add depth to our understanding of this area. Specifically, future research could explore the use of AI in other sales contexts. For example, research could explore the use outside of the development of competitive intelligence, in the context of the pre-approach, approach, or other areas within the sales funnel. Further, researchers and practitioners alike would benefit from understanding customers' perspectives on the use of AI, and the extent to which they perceive that AI creates value for them and how. Finally, this research uncovered a range of interpretations of what value AI technologies can bring and where the limitations are. Future research should explore the origins and impacts of the gap between reality and expectations regarding AI. This research could be used to develop education or training programs that will allow firms to better align customer expectations with reality.

Our research has a number of limitations. First, the findings presented in this study have limitations with respect to generalizability. As a qualitative study, this research provides analytic rather than statistical generalizability, which in itself represents a motivation and also the groundwork for future research, as numerous facets of AI-enabled value co-creation processes remain poorly understood. Our investigation focused on one start-up firm in North America, and our findings may not be generalizable to other firms. In addition, a startup is an inherently unstable form of business organization, and as a result our findings may not apply to more established organizations. Indeed, some of our findings may be more reflective of the startup context rather than of the use of AI in value co-creation in general.

While we regard all actors – employees, the bot, curators, and consumers – as co-creators of value following Vargo & Lusch (2004), others perceive the process of value creation separately from the value as an outcome of the process (e.g., Grönroos, 2011; Heinonen, Strandvik, Mickelson, Edvardsson, Sundström, & Andersson, 2010). Our informants only briefly touched on the perception of value through use of the information, as the consumer's role was only discussed in cursory terms. Future research may focus more deeply on the customer sphere, exploring how individuals perceive the co-creation of value through use after exchanging and integrating information or other resources by means of AI. We would anticipate that views could potentially vary across different hierarchical levels, departmental affiliations, or roles within the value creation process.

In keeping with the core of our research, AI might enable the analysis of 'big data' sets that are generated in technology-enabled value co-creation like the service studied in the current research (Maglio & Breidbach, 2014). The very tools used by the company, NLP and ML, are also at the core of such content analysis tools as IBM Watson and promise additional detailed research opportunities based on the data that gets generated and logged in the various stages of these transactions.

Conclusion

Artificial intelligence is well poised to make an impact on a wide range of marketing activities. In this research, we have uncovered and discussed the human and computer elements involved, the processes undertaken, and the resources needed when using AI to create value through developing competitive intelligence in a B2B sales context. Our findings reveal that even among those who provide AI based intelligence, perceptions of AI are often guided by notions popularized by both science and science fiction: that is, people perceive AI as either human-like intelligence or as threatening artificial superintelligence. Indeed, these perceptions have been popularized by notable figures such as Steven Hawking and Elon Musk (Cellan-Jones, 2017), as well as in a range of futuristic movies, television shows, and novels. Yet, the reality of a marketable AI product differs greatly from these perceptions. Not only does an 'auto-magic' button not exist, but the industry is far from developing one.

Based on our research, managers operating on the provider side will be well advised to continue managing customer expectations with respect to the capabilities of AI and the continued necessity to involve human resources in the value co-creation process. Researchers, on the other hand, should continue to contribute to the closing of this existing knowledge gap to avoid the degeneration of AI into 'just another buzzword' that failed to live up to the hype and the expectations arising from it.

This research also offers contributions to scholarly knowledge. Specifically, in this research, we have applied SDL to understand AI-enabled value which is a relatively new context. This research, therefore, helps close a gap in our understanding of value co-creation processes with new technologies, and more specifically AI, which was identified as a gap in our literature review earlier in this article. In addition, this study has helped to clarify the resources that information technologies, specifically those built on AI, can bring to value co-creation process. We have demonstrated that AI can act as an operand and operant resource at different stages of the value co-creation process in our study.

Finally – and importantly – this research shows that human actors play important and essential roles in value co-creation. Limitations to

AI technology, as well as the importance of industry specific and experience-based knowledge, lead to a situation in which the value extracted from AI is dependent upon the expertise of individuals who provide and use AI based services. Given the contributions of human actors relative to the state of AI technology, the role of humans will likely remain both important and essential for some time.

References

Anderson, W.T., Challagalla, G.N. and MacFarland, R.G. (1999), “Anatomy of exchange”, *Journal of Marketing Theory and Practice*, Vol. 7 No. 4, pp. 8–19.

Black, J.S. and Van Esch, P. (2020), “AI-Enabled Recruiting: What Is It and How Should a General Manager Use It”, *Business Horizons*, Vol. 63 No. 2.

Bottani, E., Centobelli, P., Gallo, M., Kaviani, M.A., Jain, V. and Murino, T. (2019), “Modelling wholesale distribution operations: an artificial intelligence framework”, *Industrial Management & Data Systems*, Vol. 119 No. 4, pp. 698–718.

Brashear, T., Granot, E., Brashear, T.G. and Motta, P. (2012), “A structural guide to in-depth interviewing in business and industrial marketing research. Journal of Business & Industrial Marketing.”, *Journal of Business & Industrial Marketing*, Vol. 27 No. 7, pp. 547–553.

Braun, V. and Clarke, V. (2006), “Using thematic analysis in psychology”, *Qualitative Research in Psychology*, Vol. 3 No. 2, pp. 77–101.

Breidbach, C.F. and Maglio, P.P. (2016), “Technology-enabled value co-creation: An empirical analysis of actors, resources, and practices”, *Industrial Marketing Management*, Vol. 56, pp. 73–85.

Čaić, M., Odekerken-Schröder, G. and Mahr, D. (2018), “Service robots: value co-creation and co-destruction in elderly care networks”, *Journal of Service Management*, Vol. 29 No. 2, pp. 178–205.

Cellan-Jones, R. (2017), “Stephen Hawking warns artificial intelligence could end mankind”, *BBC Technology*, 2 December, available at: http://www.bbc.com/news/technology-30290540 (accessed 14 April 2018).

Constantin, J.A. and Lusch, R.F. (1994), *Understanding Resource Management*, The Planning Forum, Oxford, OH.

Day, G.S. (1994), “The Capabilities of Market-Driven Organizations”, *Journal of Marketing*, Vol. 58 No. 4, pp. 37–52.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019), “Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda”, *International Journal of Information Management*, No. 48, pp. 63–71.

Dubé, L., Du, P., McRae, C., Sharma, N., Jayaraman, S. and Nie, J.Y. (2018), “Convergent innovation in food through big data and artificial intelligence for societal-scale inclusive growth”, *Technology Innovation Management Review*, Vol. 8 No. 2.

Eitle, V. and Buxmann, P. (2019), “Business Analytics for Sales Pipeline Management in the Software Industry: A Machine Learning Perspective”, *Proceedings of the 52nd Hawaii International Conference on System Sciences*, presented at the Hawaii International Conference on System Science (HICSS), Hawaii, pp. 1013–1022.

Fereday, J. and Muir-Cochrane, M.E. (2006), “Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development”, *International Journal of Qualitative Methods*, Vol. 5 No. 1, pp. 80–92.

Füller, J. (2010), “Refining virtual co-creation from a consumer perspective”, *California Management Review*, Vol. 52 No. 2, pp. 98–122.

Gill, N.S. (2017), “Overview of Artificial Intelligence and Natural Language Processing”, available at: https://www.upwork.com/hiring/for-clients/artificial-intelligence-and-natural-language-processing-in-big-data/ (accessed 11 December 2017).

Glaser, B.G. and Strauss, A.L. (2017), *Discovery of Grounded Theory: Strategies for Qualitative Research*, Routledge.

Grönroos, C. (2011), “Value co-creation in service logic: A critical analysis”, *Marketing Theory*, Vol. 11 No. 3, pp. 279–301.

Heinonen, K., Strandvik, T., Mickelson, K.J., Edvardsson, B., Sundström, E. and Andersson, P. (2010), “A customer-dominant logic of service. Journal of Service management”, *Journal of Service Management*, Vol. 21 No. 4, pp. 531–548.

Huang, M.H. and Rust, R.T. (2018), “Artificial intelligence in service.”, *Journal of Service Research*, Vol. 21 No. 2, pp. 155–172.

Itani, O.S., Agnihotri, R. and Dingus, R. (2017), “Social media use in B2b sales and its impact on competitive intelligence collection and adaptive selling: Examining the role of learning orientation as an enabler”, *Industrial Marketing Management*, Vol. 66, pp. 64–79.

Kaartemo, V. and Helkkula, A. (2018), “A systematic review of artificial intelligence and robots in value co-creation: current status and future research avenues”, *Journal of Creating Value*, Vol. 4 No. 2, pp. 211–228.

Kaelbling, L.P., Littman, M.L. and Moore, A. W. (1996), “Reinforcement learning: A survey”, *Journal of Artificial Intelligence Research*, Vol. 4, pp. 237–285.

Kaplan, A. and Haenlein, M. (2019), “Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence”, *Business Horizons*, Vol. 62 No. 1, pp. 15–25.

Kietzmann, J.H., Hermkens, K., McCarthy, I.P. and Silvestre, B.S. (2011), “Social media? Get serious! Understanding the functional building blocks of social media”, *Business Horizons*, Vol. 54 No. 3, pp. 241–251.

Knote, R. (2019), “Towards Smart Assistance Systems for Physical and Manual Tasks”, *Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden*, Stockholm.

Kohli, A.K. and Jaworski, B.J. (1990), “Market orientation: the construct, research propositions, and managerial implications”, *Journal of Marketing*, Vol. 54 No. 2, pp. 1–18.

Lincoln, Y. S., & Guba, E. G. (1985), *Naturalistic Inquiry*, Vol. 75, SAGE Publications.

Lusch, R.F. and Nambisan, S. (2015), “Service Innovation: A Service-Dominant Logic Perspective”, *MIS Quarterly*, Vol. 39 No. 1, pp. 155–175.

Lusch, R.F., Vargo, S.L. and Gustafsson, A. (2016), “Fostering a trans-disciplinary perspectives of service ecosystems”, *Journal of Business Research*, Vol. 69 No. 8, pp. 2957–2963.

Maglio, P.P. and Breidbach, C.F. (2014), “Service science: toward systematic service system innovation. In Bridging Data and Decisions”, *Bridging Data and Decisions. INFORMS*, pp. 161–170.

Martínez-López, F.J. and Casillas, J. (2013), “Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights”, *Industrial Marketing Management*, Vol. 42, pp. 489–495.

Meire, M., Ballings, M., & Van den Poel, D. (2017), “The added value of social media data in B2B customer acquisition systems: A real-life experiment.”, *Decision Support Systems*, No. 104, pp. 26–37.

MIT Technology Review Insights. (2018), “Professional services firms see huge potential in machine learning”, 2 November, available at: https://www.technologyreview.com/s/612374/professional-services-firms-see-huge-potential-in-machine-learning/ (accessed 31 January 2019).

Nair, R. and Narayanan, A. (2012), *Benefitting from Big Data. Leveraging Unstructured Data Capabilities for Competitive Advantage*, Booze&Co, available at: https://www.strategyand.pwc.com/media/uploads/Strategyand_Benefitting-from-Big-Data.pdf (accessed 24 January 2019).

Narver, J.C. and Slater, S.F. (1990), “The effect of a market orientation on business profitability”, *Journal of Marketing*, Vol. 54 No. 4, pp. 20–35.

Paschen, J., Kietzmann, J. and Kietzmann, T. (2019), “Artificial intelligence (AI) and its implications for market knowledge in B2B marketing”, *Journal of Business & Industrial Marketing*.

Paschen, J., Pitt, L. and Kietzmann, J. (2019), “Emerging Technologies and Value Creation in Business and Industrial Marketing”, *Journal of Business & Industrial Marketing*, pp. 1401–1402.

Paschen, J., Wilson, M. and Ferreira, J. (2020), “Collaborative Intelligence - how human and artificial intelligence (AI) create value along the B2B sales funnel”, *Business Horizons*.

Paschen, U., Pitt, C. and Kietzmann, J.H. (2020), “Artificial Intelligence: Building Blocks and an Innovation Typology”, *Business Horizons*, Vol. 63 No. 1.

Rizkallah, J. (2017), “The Big (Unstructured) Data Problem”, *Forbes*, 5 June, available at: https://www.forbes.com/sites/forbestechcouncil/2017/06/05/the-big-unstructured-data-problem/#57541ca2493a (accessed 19 December 2017).

Russell, S.J. and Norvig, P. (2016), *Artificial Intelligence: A Modern Approach*, 3rd ed., Pearson Education Limited, Upper Saddle River, NJ.

Russo-Spena, T., Mele, C. and Marzullo, M. (2019a), “Practising Value Innovation through Artificial Intelligence: The IBM Watson Case”, *Journal of Creating Value*, Vol. 5 No. 1, pp. 11–24.

Russo-Spena, T., Mele, C. and Marzullo, M. (2019b), “Practising Value Innovation through Artificial Intelligence: The IBM Watson Case.”, *Journal of Creating Value*, Vol. 5 No. 1, pp. 11–24.

Schwab, K. (2016), “The Fourth Industrial Revolution: what it means, how to respond”, *World Economic Forum - Global Agenda*, 14 January, available at: https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/ (accessed 4 October 2018).

Singh, J., Flaherty, K., Sohi, R.S., Deeter-Schmelz, D., Habel, J., Le Meunier-FitzHugh, K., Malshe, A., et al. (2019), “Sales profession and professionals in the age of digitization and artificial intelligence technologies: concepts, priorities, and questions”, *Journal of Personal Selling & Sales Management*, Vol. 39, pp. 1–21.

Strauss, A. and Corbin, J.M. (1997), *Grounded Theory in Practice*, SAGE Publications.

Syam, N. and Sharma, A. (2018), “Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice”, *Industrial Marketing Management*, Vol. 69, pp. 135–146.

Tecuci, G. (2012), “Artificial intelligence”, *WIREs: Computational Statistics*, Vol. 4 No. 2, pp. 168–180.

Van Esch, P., Black, J.S. and Ferolie, J. (2019), “Marketing AI recruitment: The next phase in job application and selection”, *Computers in Human Behavior*, Vol. 90, pp. 215–222.

Van Esch, P. and Van Esch, L. (2013), “Justification of a qualitative methodology to investigate the emerging concept: The dimensions of religion as underpinning constructs for mass media social marketing campaigns”, *Journal of Business Theory and Practice*, Vol. 1 No. 2, pp. 214–243.

Vargo, S.L. and Lusch, R.F. (2004), “Evolving to a new dominant logic for marketing”, *Journal of Marketing*, Vol. 68 No. 1, pp. 1–17.

Vargo, S.L. and Lusch, R.F. (2016), “Institutions and axioms: an extension and update of service-dominant logic”, *Journal of the Academy of Marketing Science*, Vol. 44 No. 1, pp. 5–23.

Vargo, S.L., Maglio, P.P. and Akaka, M.A. (2008), “On value and value co-creation: A service systems and service logic perspective”, *European Management Journal*, Vol. 26 No. 3, pp. 145–152.