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Enabling Value co-creation with customers through Artificial Intelligence: A case study approach

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ENABLING VALUE CO-CREATION WITH CUSTOMERS THROUGH ARTIFICIAL INTELLIGENCE: A CASE STUDY APPROACH

Research in Progress

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Abstract

The digital movement has radically altered how manufacturing companies interact with their customers. By using Artificial Intelligence (AI), companies have drastically changed their value co-creation (VCC) strategies. We adopt a case study approach and engage with an original equipment manufacturer (OEM) to get a grasp of the phenomenon. Among the data collection methods we assume, we conduct semi-structured interviews with the company project team and its customer base. In addition, we collect secondary data and run focus groups within the studied firm's management team. This research in progress will advance a framework linking VCC with service maturity and identify the performance metrics required for the AI-based journey. Such a framework may assist practitioners in building services based on AI and VCC. Ultimately, we plan to offer theoretical implications to progress the AI and VCC debate and propose future research suggestions.

Keywords: Value Co-Creation (VCC), Artificial Intelligence (AI).

1 Introduction

Traditional company approaches have been to provide value to customers through producing products and services (Lusch, 2011). The customers would then benefit by consuming these products and services. However, the rise of the VCC notion has led firms to rethink how they produce value by actively seeking to involve the customers in the process (Lusch, 2011). Through such a collaboration, VCC stems from equally useful links among different actors (Kohtamäki and Rajala, 2016).

As Original Equipment Manufacturers (OEMs) attempt to concentrate their attention on VCC, new challenges arise as such an undertaking demands advancing and maturing novel competencies (Sjödin et al., 2016, Wallin et al., 2015). Furthermore, with the advent of enabling technologies such as AI and Big Data, the digital movement has accelerated the change in how firms operate (Porter and Heppelmann, 2014). For instance, OEMs can now connect and incorporate unique features to drive VCC occasions with their customers (Porter and Heppelmann, 2014).

This digital paradigm emanates from merging enabling technologies with company processes and actors with likely repercussions on existing equilibriums (Hinings et al., 2018) and novel approaches to achieve business profitability (Teece, 2018). Besides, the technologies' uniqueness has allowed multiple actors to produce new value propositions (Hinings et al., 2018). As technological advances accelerate the transformation of established industries, causing new complexities, companies must prioritize managing this uncertainty (Teece, 2018). In short, digital transformation has disrupted how industrial organizations collaborate with diverse actors to create and capture value (Teece, 2018, Porter and Heppelmann, 2014).

Recently, AI has been one of the most promising technologies, receiving increased academic and industry-led engagement regarding value creation and co-creation (Enholm et al., 2022). Companies expect a profound effect of AI on their offerings and perceive AI introduction as a strategic competitive advantage (Ransbotham et al., 2017). Furthermore, AI promises industrial firms the potential to reconfigure their service offerings (Wiener et al., 2020) with wide-ranging impacts on the corporate world and economies. AI offers them exceptional possibilities for innovation (Berente et al., 2021) and for gaining unique customer insights and perspectives (Paschen et al., 2021). More importantly, customers must get deeply involved with AI-based solutions in co-creating these solutions (Marcos-Cuevas et al., 2016).

However, despite the empirical studies tackling VCC and digital technologies (Ramaswamy and Ozcan, 2018), we observe a gap in how AI may influence VCC (Berente et al., 2021, Leone et al., 2021, Paschen et al., 2021, Kaartemo and Helkkula, 2018). Some have explained this limited impact that firms grapple with developing their AI strategies to achieve AI capabilities that can deliver precise and substantiated results (Enholm et al., 2022, Fountaine et al., 2019). Others have proposed that many firms must fully grasp the components of digital capabilities and require help to create value with their client base (Lenka et al., 2017).

Research on AI has mainly emphasized how AI can support a service provider. For example, AI can help predict much more accurately market changes than standard techniques (Barrow, 2016). Scholars have also examined the effects of AI on human-to-machine interactions. Glushko and Nomorosa (2013), for instance, explored mechanisms that help companies decide when an AI-enabled interaction creates value in a service. In addition, research on AI-based solutions and VCC have examined the instances when AI-based solutions can replace a human (Kot and Leszczyński, 2022) and the roles that the different users interacting with the AI-based solutions must perform to unleash its potential (Paschen et al., 2021). While the literature has emphasized AI-driven opportunities, limited studies address the means and methods organizations may adopt to co-create value from AI with their customers (Duan et al., 2019).

Thus, this research-in-progress aims to contribute to the management and information systems academic debates by investigating the co-creation mechanisms when adopting AI-based offerings. Since the context plays a specific function in decoding and acting on AI-generated information (Berente et al., 2021), we concentrate our research on an industry where VCC endeavors are scarce. By adopting a single-case research design, we undertake to interpret the VCC phenomenon better to theorize and depict the co-creation process actors may adopt (Kohtamäki and Rajala, 2016). More specifically, we aim to identify the following:

RQ: How can original equipment manufacturers (OEMs) use AI to stimulate co-creating value with customers?

From a theoretical viewpoint, one of the critical contributions of our research is answering the call of many scholars to conceptualize value creation by adopting the AI lens (Kaartemo and Helkkula, 2018, Marcos-Cuevas et al., 2016, Leone et al., 2021, Kohtamäki and Rajala, 2016, Kot and Leszczyński, 2022, Berente et al., 2021). Our research aims to deliver a framework linking VCC with service maturity. This framework seeks to identify the performance metrics required for the journey based on the four AI types defined by Huang and Rust (2018).

Practitioners may also benefit from this study as it seeks to offer managers a deeper understanding of the means and methods they require to establish services based on AI and VCC. In addition, such an overview may be helpful to practitioners before undertaking an investment decision to initiate a new AI-based service.

2 Current Understanding

2.1 Value Co-creation (VCC)

VCC occurs when the customer and supplier have a symbiotic relationship (Sheth, 2019). Lusch and Vargo (2006) proposed that "value can only be created with and determined by the user in the 'consumption' process and through use or what is referred to as value-in-use. Thus, it occurs at the intersection of the offerer and the customer over time: either in direct interaction or mediated by a good […] (goods are distribution mechanisms for service provision)."

Ramaswamy and Ozcan (2018) advance that VCC may only happen when firms extensively manage the arising collaboration from multiple stakeholders. In the service-dominant (SDL) logic proposed by Vargo and Lusch (2004), the value creation process incorporates the customers' experience when consuming the products and services. The customers then become closely related to the supplier and contribute to advancing their personal value experience (Lusch, 2011). The SDL provides, in practice, an actual conceptualization of the markets as a network of systems where each stakeholder becomes a factor in value creation (Kohtamäki and Rajala, 2016).

Lenka et al. (2017) further the debate by proposing two key capabilities essential to achieving VCC. On the one hand, firms need to devise ways to sense customers' needs to capitalize on them. On the other hand, firms must enhance their response capabilities to ensure they react to ever-changing customer needs timely (Lenka et al., 2017). Literature has provided different conceptualizations of VCC. For instance, Ranjan and Read (2014) have conceptualized VCC as co-production and value-in-use.

Co-production indicates an active involvement of the customer in the creation phase (Ranjan and Read, 2014). Ranjan and Read (2014) operationalize the creation phase into three constructs: knowledge, equity, and interaction. Knowledge encapsulates the need for customers to share information to advance new findings and stimulate creativity. Equity addresses the general readiness of various parties to break their control boundaries to foster a common interest approach. Finally, interaction enables extensive exchange between participants to learn and adapt the service based on real experiences.

Value-in-use focuses on when the customer consumes the product or service (Ranjan and Read, 2014). Ranjan and Read (2014) operationalize value-in-use into experience, personalization, and relationship. Experience allows the users (or customers) to extract intrinsic value by interacting with the artifact provided by the OEM. Personalization explains the inherent nature of experiencing the service through individual lenses and characteristics. Finally, the relationship drives cooperative attitudes and reiterative progressions, bolstering value-creation sequences.

Scholars have proposed a beneficial connection between VCC and performance, thus implicitly portraying that co-creation should be the preferred choice for firms (Kohtamäki and Rajala, 2016). However, interestingly, another line of research has argued that VCC might have adverse outcomes and benefits (Gligor and Maloni, 2021).

2.2 Value Co-Creation (VCC) in the Digital Age

Sheth (2019) indicates that one of the types of value-creation includes breakthrough innovation. Through the widespread of new technologies, companies have created a new form of values that needed to be more present or were unreachable in the past (Sheth, 2019). In addition, technology advancements provide supplementary tracks to engage and include customers as co-creators (Wang et al., 2016). In extreme cases, technological advances have disrupted industries and reorganized VCC networks (Leone et al., 2021). It is, therefore, no surprise that numerous industrial organizations have aligned their resources to utilize the potential presented by digital transformation (Teece, 2018).

Scholars have highlighted the divergence of VCC when adopting digital technologies (Kot and Leszczyński, 2022). The complexity of combining digital technologies in VCC has led to limited empirical studies (Leone et al., 2021, Kot and Leszczyński, 2022, Kaartemo and Helkkula, 2018). AI depends on the establishment of enabling technologies such as IT systems, mobile applications, and digital platforms to perform and provide worthy outputs (Paschen et al., 2021). By combining all the available data, AI applications will learn from data and extract valuable insights (Leone et al., 2021). OEMs must therefore understand the types of novel competencies required when adopting digital technologies to drive VCC from AI-based solutions.

Literature has pointed out that providers must nurture two critical instruments for VCC when adopting digital technologies (Lenka et al., 2017). On the one hand, service providers must be able to sense their customer needs development and reflect this know-how into their organization (Lenka et al., 2017). On the other hand, however, service providers must quickly translate their findings by proactively enacting valuable offerings (Lenka et al., 2017).

2.3 Artificial Intelligence (AI)

AI is an ever-developing and continuously improving computing potential that differentiates itself from any IT artifacts we have seen (Berente et al., 2021). For instance, while Big Data originates from the established practice of delivering multifaceted insights to decision-makers (Elia et al., 2020), AI departs from a different philosophy of automating tasks and improving continuously (Enholm et al., 2022). Instead, AI uses different BD sources and analytical capabilities to derive value (Ransbotham et al., 2017).

Huang and Rust (2018) have determined four specific types of AIs by adopting a historical development lens. These AI types are "mechanical, analytical, intuitive, and empathetic" (Huang and Rust, 2018). On the lower and least advanced spectrum, mechanical AI is the automated ability to conduct routine tasks (Huang and Rust, 2018). On the highest part of the spectrum and the most advanced one, empathetic AI represents the ability of the machine to understand emotions and respond accordingly (Huang and Rust, 2018).

Each type of AI capitalizes on the previous level of AI and provides wider opportunities for service applications (Huang and Rust, 2018). In addition, the types of human skills required at each AI level present a crucial differentiation originating from the different AI types (Huang and Rust, 2018).

To drive business value from AI, firms must comprehend the processes required for training AI applications and the types of data the algorithms need (Ransbotham et al., 2017). In addition, this engenders a degree of engagement that a customer has to provide to enhance the value development from the AI solution (Marcos-Cuevas et al., 2016).

3 Research Methodology

We conduct case study research on an OEM in the industrial sector that attempts to provide a service founded on data exchange and AI (referred to as "Company X"). This service will enable the users to forecast better the spare parts needs for their industrial assets, thus reducing out-of-stock situations, enhancing operational excellence, and maximizing asset utilization. We adopted the case study method as it will enable us to untie the complexities of a firm and identify how various actors in their daily work will help us learn on this topic (Stake, 1995). In addition, following qualitative research caters more to investigative questions than quantitative study (Yin, 2009).

3.1 Research Setting

In line with our research question of understanding how firms can use AI to co-create value with their customers, we assume an inductive case study design. Case studies permit the extraction of critical insights into complex relational dynamics and are predominantly valuable in developing theories from unique occurrences (Edmondson and McManus, 2007).

We collect data from the OEM and their customer base regarding the service the OEM aims to introduce. Such a dyadic data collection will allow a profound comprehension of the VCC process and matches Chesbrough et al. (2006)'s call to investigate both sides of the relationship to extract contextual significance and develop different phases.

The selected customers are either world-leading operators or repair organizations specialized in maintaining the products provided by the OEM. Both operators and repair organizations possess engineering, planning, and supply chain organizations, thus showcasing deep knowledge in the maintenance and repair of these types of equipment and possessing relatively stable established processes.

3.2 Data Collection

We begin our data collection by conducting a series of focus groups that includes a multifunctional team of leaders within Company X. The multifunctional team at Company X supports the project team in service creation. They come from leadership roles in product management, commercial, and digital functions and thus exhibit a rounded and comprehensive view of the service introduction journey. This starting stage will enable the researchers to sharpen the problem statement. Moreover, we collect secondary data that we analyze on an ongoing basis. The secondary data includes all the documents compiled by the project team related to this new service. Since the project team will discuss their service activities with some customers, the secondary data will enable the researchers to identify the challenges and opportunities for using AI to enable VCC. Next, we continue our investigation by conducting semi-structured interviews with the project team. Reaching this stage will allow us to discuss the service prototype that the project team is developing. We aim to present this prototype during our interviews with the customers. The authors have planned to conduct 32 interviews with key informants.

The authors identified the informants through a stratified sample depending on certain features and characteristics identified during the focus group stage. The informants must belong to the repair and maintenance organization in the planning, supply chain, or procurement function. The informants possess either a deep experience (10+ years) or a high level of seniority in their companies. Such an interviewee profile will enable the researchers to ask holistic questions and collect more qualified responses. In addition, these informants will help provide their views on implementing an AI-based service that fosters VCC. We plan to end the data collection process once we achieve theoretical saturation (Corbin and Strauss, 1990, Lincoln and Guba, 1985). Table 1 presents the current plan to conduct our data collection methods and how each will contribute to answering the research question.

We use semi-structured interviewing in our research methodology, as the research question will guide our inquiry instead of the hypotheses (Morrow, 2005). As Morrow (2005) explains, qualitative research questions represent the “How” type of questions to understand and interpret the social meaning of the studied topic. In addition, we focus more on the interviewee's point of view. That signifies that we have devised a set of questions on relatively defined topics we aim to bring from interview to interview.

To construct the interview guide, we relied on the feedback from three academic experts in AI and two AI professional experts from Company X. The academic experts helped us refine the questions to fit the research methodology. Company X's experts helped us pinpoint specific angles when implementing AI within that industrial context. Since these two experts have actively worked and introduced AI-based solutions, they possess first-hand insights into the limits of AI within that particular industry. As a result, we concluded that our interview session with each interviewee would consist of two main parts.

At first, the interview guide aims at understanding initially the current systems to conduct material demand forecasting. For example, we will ask informants questions such as: How do you identify the needed material parts by your organization for planned & unplanned maintenance? What data sources and systems your company uses to enable you to complete the demand forecasting task? What are your priorities & targets when conducting material demand forecasting? In your opinion, what are the key components that would enable you to deliver on your targets? Where do you see today the challenges in material demand forecasting? Where do you see the opportunities?

In the second half of the interview, the authors will present a prototype of a predictive maintenance solution that relies on data exchange and AI and extract the informant's views on such a prototype. In our quest to extract insights from the informants during the interview, we will encourage them to keep an overview of the overall material planning exercise. We will also ask them to elaborate on specific process steps to capture the similarities and differences across customer profiles. Finally, to relieve confirmation bias when presenting the prototype, we will focus on repeating critical features mentioned by the informant during the initial part of the interview and ask them how they think the prototype may affect these features.

Stage	**Stage 1**	**Stage 2**	**Stage 3**
Data collection	Focus groups	Semi-structured interviews	Semi-structured interviews
Timeline	Fall 2022	H1-2023	H1-2023
Status	Complete	In Progress	In Progress
Purpose	Gather a deep understanding of the context.	Understand VCC’s challenges, and opportunities based	Discussing the prototype and identifying the VCC mechanishm through using AI

		on the prototype that illustrates the case.	
Informants roles	Company X informants coming from leadership roles in product management, commercial, and digital functions.	Project Team at Company X	The informants belong to the repair and maintenance organization, either in the planning, supply chain, or procurement function. They possess either a deep experience (10+ years) or a high level of seniority in the companies they work for
Number of informants involved	13	6	20
Number of companies involved	One: Company X	One: Company X	15 customers of Company X representing an operator of Company X product or a specialized repair and maintenance organization in Company X product
Total interviews	3	9	20
Average interview length	68 minutes	To be determined	To be determined

Table 1. Data Sources and Collection Efforts

3.3 Data Analysis

We will base our data analysis on a thematic analysis approach, allowing us to uncover patterns in sizeable and intricate data sets (Braun and Clarke, 2006). The thematic analysis will also enable us to accurately recognize recurring themes within the specific context we are researching. In this initial step of the data analysis, we will analyze the transcripts, code the terms stated by the informants, and find the themes expressed by the interviewees.

Next, we will scrutinize the resulting themes to distinguish their patterns and associations. By conducting extensive comparisons repeatedly, we will group the empirical themes into specific conceptual categories that reflect the theoretical constructs found in the literature (Strauss et al., 2015). We pay particular attention that the data we have collected and analyzed into themes and patterns will lead us to "theoretical saturation" (Glaser and Strauss, 2017).

Finally, we will group the conceptual categories into aggregate dimensions (Gioia et al., 2013), thus pursuing a three-step process in our data analysis (Gioia et al., 2013, Braun and Clarke, 2006). Finally, we aim to present our data in a practical graphical visualization depicting the progress from our first-order concepts to the aggregate dimensions, thus replicating Gioia et al. (2013) data structure approach.

4 Preliminary Observations

Stage 1 of the data collection period offered exciting insights into this new service and helped the researchers understand the problem statement. We could also recognize that the discussions point toward specific themes found in the literature. Although we state some preliminary observations in this section, we recognize the need to progress more in our study to extract the critical findings that will help us answer our research question. For example, we observed that questions about the business model frequently arose, such as if Company X should adopt a subscription fee model or provide the service free of charge. For instance I4 mentioned:

> *We need to be a bit more specific what we want to achieve here. It could be very wide and demand forecast is always a nice concept. Making the link between the company event and really the need in term of spare … and the way we will proceed is for me a very big ambition where we have potentially some intermediate steps. So I will be a bit careful not setting the success before understanding the different steps. And maybe*

> *some intermediate step could be already a good achievement to get confidence in the way we build that.*

We could already identify in the vast literature papers addressing this specific angle of designing and commercializing business models from VCC, e.g., Kohtamäki and Rajala (2016), Sjödin et al. (2020), and Storbacka et al. (2012).

Another classic debate we encountered in the exchanges concerning this service is data sharing issues. Moving toward collecting data in large quantities and acceptable quality will lead AI to create new observations and capitalize on the network effects (Leone et al., 2021, Elia et al., 2020). Elia et al. (2020) introduce Big Data as a term with strong attention from the research and practitioner community. Big Data refers to the vast volumes of data companies can collect through the interconnectivity of different technologies, leading traditional information technologies to reach their processing and analytical limitations (Mikalef et al., 2018). Big Data has received numerous definitions in literature (7Vs: Volume, Velocity, Variety, Veracity, Value, Variability, Visualization) (Mikalef et al., 2018). The quest by organizations to amass and analyze large quantities of data may "open new technological and organizational challenges that make companies and organizations more flexible, open, creative, resilient, and competitive." (Elia et al., 2020).

Sivarajah et al. (2017) conceptualize Big Data challenges into data, process, and management-specific challenges in their systematic literature review. While data and process-specific difficulties relate to the technical aspects of using, extracting, and analyzing Big Data sources, management challenges concern the governance, privacy, and security of Big Data (Sivarajah et al., 2017). AI is perceived as a technology that solves the technical challenges inherent to Big Data and is proficient in data analysis and extraction (Duan et al., 2019). However, despite the technological advancements, AI-based applications still depend on some hurdles the service provider must tackle (Duan et al., 2019). For instance, Davenport and Ronanki (2018) have highlighted that companies must properly comprehend the AI-based solution's capabilities and limitations before adopting it.

Another recurring topic from the exchanges conducted involved ecosystem and platform literature. Interestingly, I1 mentioned:

> *we can see that just setting up a platform [...] communicating about it, try to attract sellers and buyers. That is not what the customer want. They simply want to interact with a seller or a buyer on their own platform and that's where we need to set up the entire digital sourcing and that we can do by first and foremost we need to detail the customer journey. We need to understand their pain points and then we also need to utilize some of the technologies that we have where we can see we can actually improve their way of working, making it easier for them to conduct their business*

The SDL approach explicates that value creation arises from collaboration and incorporation between the producer and customers in an ecosystem (Lusch et al., 2016). Ecosystems are particular types of shaping economic pursuits (Jacobides et al., 2018). Indeed, all collaborating firms are interdependent with specific complementary types that control the value types (Jacobides et al., 2018). Adopting the service network as the unit of analysis represents a departure from the traditional approaches found in literature where firms or supplier-customer relationships have been the focus (Kohtamäki and Rajala, 2016).

5 Limitations and Future Research

While we follow a systematized and in-depth research methodology, we recognize that our current research in progress presents some limitations. First, although the three focus groups conducted in stage 1 of the research include 13 senior leaders of the industry with in-depth industry expertise combining different functional angles, their views may need to be more representative. Our informants from this stage all belong to Company X and therefore depict only one aspect of the picture. We plan to address this through stage 3 of the study. Through our discussions with Company X's customers, we will pay careful attention if we encounter a dissonance between what they need and what Company X thinks customers want. These insights we collect from the dyadic interview approach may provide fascinating wisdom into the VCC mechanisms.

In addition, we remain cautious on the premise that Company X can be the central hub in connecting to its customers by pushing its service or system through. Company X's customers may need more time to explore such a service. We aim to investigate this aspect in stage 3 of the study.

Finally, as the actors of Company X are deeply involved in the development of the service, some statements may point clearly to the direction of value co-production. However, the value-in-use aspects may have gathered less consideration because customers differ in their operations, size, digitalization, maturity, and other aspects. We aim to resolve this shortcoming through the interviews in stages 2 and 3. Stage 2 will allow us to extrapolate firsthand the experience faced by the project team through their active customer-facing interactions of presenting the service, collecting feedback, and updating the features. Stage 3 will include varied customer profiles representing the entire supply chain process.

As we continue our research in the coming months, we will endeavor to strike a balance between our grasp of the events and providing testimony in the form of quotes from interviewees (Morrow, 2005).

6 Expected Contribution

This research is an early attempt to address some rising questions in the AI field. The researchers are still conducting their interviews and aim to complete the data collection in the first half of 2023. After that, the researchers will analyze the collected data through the abovementioned methodology to solve the research question introduced.

Among the various theoretical contributions, we aim to develop a conceptual model that would encapsulate the multiple themes that arise along with the linking relationships (Morrow, 2005). For example, conceptualizing value creation by taking the AI lens has been a call for research by many scholars (Kaartemo and Helkkula, 2018). Moreover, through the conceptual model, we endeavor to identify if and how AI-augmented solutions mediate the customer journey (Kaartemo and Helkkula, 2018).

One key finding we embark on unwrapping addresses the future limits of AI that Berente et al. (2021) postulated. Our case study contemplates how OEMs can influence engineering and supply chain processes by combining AI into the equation (Berente et al., 2021). As pointed out as well by Berente et al. (2021), the context plays a specific role in interpreting and acting on AI-generated information. We strive to offer some findings related to that angle by focusing on an established manufacturing sector.

Last, Enholm et al. (2022) highlighted a research gap in differentiating between how firms may implement performance metrics to encapsulate AI effects according to external or internal AI use. Through our case study, we endeavor to uncover and understand the performance metrics applicable for VCC on AI applications with customers.

From a practical point of view, this research will suggest several managerial implications. First, the contribution could benefit Company X in understanding the means and methods required to establish the services based on AI and VCC. Second, we will develop the framework following the insights of several actors in this particular manufacturing context which could present other OEMs with a reliable and hands-on benchmark on how they may introduce more AI-based services. Finally, OEMs may explore this case study to identify the performance metrics needed for AI-based VCC applications.

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