The Dark Side of AI-powered Service Interactions: Exploring the Process of Co-destruction from the Customer Perspective

Daniela Castillo*
Daniela.Castillo@brunel.ac.uk
+356 2340 3478
ORCID ID: https://orcid.org/0000-0001-7673-2388

Doctoral Researcher
Brunel Business School
Brunel University London, Uxbridge, UB8 3PH, United Kingdom

Assistant Lecturer
Department of Marketing
Office 431, Faculty of Economics, Management and Accountancy, University of Malta, Msida MSD 2080, University of Malta
Malta

Ana Isabel Canhoto
Ana.Canhoto@brunel.ac.uk
+44(0)1895 232806
ORCID ID: https://orcid.org/0000-0002-1623-611X

Reader in Marketing
Brunel Business School
Brunel University London, Uxbridge, UB8 3PH, United Kingdom

Emanuel Said
Emanuel.Said@um.edu.mt
+356 2340 3477
ORCID ID: https://orcid.org/0000-0002-6481-6258

Head of the Marketing Department
University of Malta
Office 413, Faculty of Economics, Management and Accountancy, University of Malta, Msida MSD 2080, Malta

*Corresponding Author

The Dark Side of AI-powered Service Interactions: Exploring the Process of Co-destruction from the Customer Perspective

Abstract

Artificial intelligence (AI)-powered chatbots are changing the nature of service interfaces from being human-driven to technology-dominant. As a result, customers are expected to resolve issues themselves before reaching out to customer service representatives, ultimately becoming a central element of service production as co-creators of value. However, AI-powered interactions can also fail, potentially leading to anger, confusion, and customer dissatisfaction. We draw on the value co-creation literature to investigate the process of co-destruction in AI-powered service interactions. We adopt an exploratory approach based on in-depth interviews with 27 customers who have interacted with AI-powered chatbots in customer service settings. We find five antecedents of failed interactions between customers and chatbots: authenticity issues, cognition challenges, affective issues, functionality issues, and integration conflicts. We observe that although customers do accept part of the responsibility for co-destruction, they largely attribute the problems they experience to resource misintegration by service providers. Our findings contribute a better understanding of value co-destruction in AI-powered service settings and provide a richer conceptualization of the link between customer resource loss, attributions of resource loss, and subsequent customer coping strategies. Our findings also offer service managers insights into how to avoid and mitigate value co-destruction in AI service settings.

Keywords

Value Co-destruction; Customer Resource loss; Artificial Intelligence; Automated service interactions; Chatbots; Service Robots; Value Co-creation

Word Count

9,048 words (excluding References)

Introduction

Artificial intelligence (AI) is rapidly transforming service encounters, as frontline employees (FLEs) are increasingly becoming supported or even replaced by AI technology. Indeed, automated customer service agents attracted the highest share of AI investment (USD4.5 billion worldwide) in 2019 (IDC, 2019). Such technologies, which include conversational agents (or chatbots) and voice-controlled digital assistants (e.g., Alexa), are fundamentally changing the nature of the service interface from one that is human-driven to one that is predominantly autonomous and technology-dominant (Larivière et al., 2017).

By interacting with AI technologies to self-serve, a customer becomes a central element of service production, a 'partial employee' and a co-creator of value (Bitner et al., 1997; Vargo & Lusch, 2004). Active customer participation during service encounters yields several benefits. For service providers, it results in an improved ability to understand and react to customer needs (Etgar, 2008), while customers value the convenience and the cost savings afforded by such technologies (Ho & Ko, 2008). AI technologies can also provide more convenient, accessible services compared to the more 'traditional' services they substitute, generally enabling customers to accomplish specific tasks more easily.

However, positive value creation is not the only outcome that can arise when customers interact with AI-powered technologies. In the same way that value is collaboratively co-created, it can be collaboratively co-destroyed during the process of interaction (Echeverri & Skålén, 2011). The autonomy of AI may signify suboptimal outcomes if the technology adapts in unexpected ways or the wrong data is acted on by FLEs or customers (Bock et al., 2020). Furthermore, AI technologies rely on customer participation, which increases service complexity and, eventually, the likelihood of service failure (Hilton & Hughes, 2013). As customers invest higher levels of effort and time into an interaction, they might feel annoyed and frustrated when the co-created service fails to meet their expectations (Grönroos & Voima, 2013; Harrison & Waite, 2015). Indeed, these instances represent the loss of valuable resources, such as time and patience, for the customer (Harrison & Waite, 2015).

Academic literature to date has offered an incomplete understanding of the antecedents of co-destruction and resource loss in particular (Järvi et al., 2018; Smith, 2013). Further research on value co-destruction is required to obtain a more complete and refined appreciation of the processes involved (Ostrom et al., 2015). Such an understanding is especially important in light of the pervasiveness of AI technologies in service, particularly regarding conditions and drivers that determine how AI may lead to diminished value creation (Bock et al., 2020).

We aim to understand the process of co-destruction in AI-powered service interactions and argue that such extant literature does not offer sufficient insights into this topic. This is a potential result of three research limitations.

First, whereas value co-creation has been given considerable research attention (e.g., Cova & Dalli, 2009; Morosan & DeFranco, 2016; Ramaswamy & Ozcan, 2018; Verleye, 2015), co-destruction has been largely overlooked (Ostrom et al., 2015). The limited research addressing co-destruction has generally focused on conceptual discussions of the notions of co-destruction and the associated resource loss (e.g., Echeverri & Skålén, 2011; Plé & Chumpitaz Cáceres, 2010), with few studies empirically examining resource loss and its causes (e.g., Smith, 2013). Customers are increasingly playing a more significant role in service delivery, as service encounters are becoming increasingly infused with technology and automation. We argue that, as a result of this trend, a better understanding of the antecedents of value co-destruction, especially customer resource loss, is required. This understanding is especially important to ensuring that co-destruction is avoided, especially in service encounters that are specifically designed to foster value co-creation (Plé, 2017).

Second, what we do know about co-destruction comes from traditional service settings, such as insurance (Blut et al., 2019). There have been calls for further research on value co-destruction in a diversity of industries and contexts (Prior & Marcos-Cuevas, 2016), especially in technology-driven service environments (Quach & Thaichon, 2017). Ostrom et al. (2015) propose that rapid changes in service experience and delivery that are being brought about by technology necessitate novel service-related knowledge. Evolved service encounters create an opportunity to evaluate how AI affects core service areas, such as co-creation and co-destruction (Robinson et al., 2020).

Third, a consumer-centric understanding of value co-destruction remains limited (Camilleri & Neuhofer, 2017; Yin et al., 2019). Most co-destruction studies examine provider–customer relationships in Business-to-Business (B2B) settings (Echeverri & Skålén, 2011; Järvi et al., 2018; Vafeas et al., 2016), whereas few studies focus on the customer perspective (Kim et al., 2019; Smith, 2013). Service-Dominant (S-D) logic proposes that 'value is uniquely and phenomenologically determined by the beneficiary' (Vargo & Lusch, 2008, p. 7). However, research examining how consumers individually experience value creation and destruction remains scarce (Kelleher & Peppard, 2011). We argue that it is vital to understand the antecedents of customer resource loss from the customer point of view, especially in AI-powered self-service settings, where the customer lies at the very core of service delivery.

Our study seeks to help close these gaps by investigating the process of co-destruction in AI-powered service settings. We aim to address two distinct objectives: first, to understand the transformational effects of AI on co-destruction, and second, to analyze the process of co-destruction from the customer perspective. We draw on an in-depth empirical study based on 27 interviews with customers who have already interacted with AI-powered chatbots. We propose a conceptualization of the co-destruction process through AI technology to demonstrate the link between customer resource loss, attributions of resource loss, and customer coping strategies following such loss.

In the coming paragraphs, we first discuss how AI is transforming the service industry. We then explore the theoretical concept of value co-destruction by adopting an S-D logic lens. Then, we discuss the research method before presenting our findings and discussing the proposed conceptualization of co-destruction in AI service settings. We offer theoretical contributions for value co-destruction research, as well as managerial implications for the service industry based on our findings.

Theoretical Background

AI in Service Encounters

The extant literature generally describes AI in terms of human intelligence or mimicking intelligent human behavior, and involving a number of cognitive functions, such as rational thinking, problem-solving, and learning (Huang & Rust, 2018; Syam & Sharma, 2018; Tussyadiah, 2020). Distinct abilities of AI have been proposed in relation to the human skills that can be reproduced. Huang and Rust (2018) discuss four different types of intelligence needed for service tasks: mechanical, analytical, intuitive, and empathetic. Mechanical intelligence is related to repetitive mundane tasks, which are exemplified by those performed by call center agents. Analytical intelligence concerns the ability to process information for problem-solving and learning. It depends largely on machine learning (ML)—a subset of AI that allows systems to automatically learn and improve from past experiences without being explicitly programmed to do so. Intuitive intelligence is associated with creative thinking and problem-solving, such as that required by marketing managers and doctors. Empathetic intelligence refers to one's ability to identify and comprehend others' emotions and respond accordingly. Empathic intelligence is central for those whose occupations require interpersonal and people skills, such as psychologists.

Chatbots, or conversational agents, are examples of AI applications that are being deployed in service settings that are of a mechanical or analytical nature. A conversational agent is a virtual, autonomous, technological object that can engage in proactive or reactive behavior (Holz et al., 2009). Chatbots are a type of disembodied conversational agent, as they do not have a physical appearance; they allow user interactions through only voice or text interfaces (Araujo, 2018; Keyser et al., 2019). However, not all chatbots are AI-driven. For instance, rule-based chatbots are scripted with pre-programmed logic and follow a predetermined path of questions and answers, exhibiting minimal intelligence (Tuzovic & Paluch, 2018). Such entry-level chatbots can be implemented to answer Frequently Asked Questions (FAQs), such as delivery and shipping-related questions (Buhalis & Cheng, 2020). By contrast, AI-driven chatbots are capable of understanding and communicating via human language through natural language processing (NLP) (Griol et al., 2013). Additionally, ML allows chatbots to continuously learn and evolve as they obtain access to increased amounts of data (Kumar et al., 2016).

Examples of AI-driven chatbots include virtual assistants Alexa (Amazon), Siri (Apple), and Edward (made available by Edwardian Hotels). Edward can communicate in natural, conversational language to guide tourists throughout their entire travel journey, and it learns from every interaction (Tussyadiah, 2020). In 2019, Edward managed 69% of all guest queries, resulting in increased efficiency and the re-assignment of staff from repetitive tasks to more important queries (Oram, 2019).

The information-rich nature of the service industry is a possible reason for the widespread adoption of chatbots by companies (Kumar et al., 2016), as companies are constantly striving to streamline their operations and achieve cost savings (Ukpabi et al., 2019). In service settings, chatbots can create a prompt, interactive, convenient, and cost-effective channel for communicating with customers throughout their entire journey (Belanche et al., 2020; Chung et al., 2018; Gnewuch et al., 2018).

Despite companies' increased enthusiasm for chatbot deployment, a number of important questions have emerged, including the potential for chatbots to significantly affect relationships between customers and service providers at the service frontline (van Doorn et al., 2017). Chatbots have the ability to either augment or substitute frontline service employees (Davenport et al., 2019). The literature suggests that AI technologies can assist FLEs by helping them perform their roles better, or they can completely replace and automate employees' active involvement in service encounters (Keyser et al., 2019; Marinova et al., 2017). Several studies have challenged the classic idea that augmentation and substitution are mutually exclusive, as both effects can emerge simultaneously during the adoption of a technology (e.g., Ivanov & Webster, 2019). Thus, AI technology will always have an impact on a significant portion of service encounters.

There is growing evidence showing that, while AI-powered chatbots can enrich the customer experience by learning from previous customer conversations and continuously adapting their responses from such learning (Xu et al., 2017), they can also cause discomfort (Mende et al., 2017). Studies of human–computer interaction have reported that when chatbots are designed to be more complex and animated, exhibiting high levels of anthropomorphism, customers experience the negative feelings of eeriness and unease (Ciechanowski et al., 2019). Negative emotions can lead to negative attitudes towards a service provider with resultant—and often irreversible—reduced purchase intentions (Demoulin & Willems, 2019). Thus, identifying the conditions under which chatbots can undermine the customer experience is an urgent objective.

Value Co-creation and Co-destruction in Technology-Driven Service Encounters

When interacting with technology to self-serve, customers adopt a critical role in service production. In this role as partial employees and active co-creators of value, customers become fully engaged in solving problems and delivering the required service (Bitner et al., 1997). Here, we will draw on the value co-creation literature to understand the antecedents to value loss in AI-powered service encounters.

Value co-creation implies that value and experiences can no longer be merely delivered to customers; rather, the service provider can only present value propositions (Vargo & Lusch, 2008). Once customers accept such propositions and successfully integrate their operant and operand resources, value is co-created collaboratively and interactively (Chandler & Lusch, 2015; Hilton & Hughes, 2013). In an AI-driven service encounter, the service provider can only create a value proposition that includes the availability of the chatbot, together with a number of modules, such as the user interface, the knowledge base, and the NLP interpreter module, in order to be able to read, understand, and derive meaning from human language (Buhalis & Cheng, 2020). It is the customer, through the integration of operand and operant resources (e.g., skills, time, and access to mobile phone and the Internet), who seeks to collaborate (i.e., interact) with the chatbot and, as a result, determine value creation. For example, instead of engaging in face-to-face interactions with a receptionist at a hotel, customers can get in touch with an AI-powered chatbot that is able to answer queries at any time of the day, irrespective of the customer's location or language. Such individualized, contextualized experiences based on instant dynamic engagement between the customer and the service provider are examples of real-time value co-creation (Buhalis & Sinarta, 2019).

The premise of a collaborative process of co-creation between a service provider and a customer has recently attracted criticism, since it inherently implies that interactions between the two actors tend to result in value co-creation (i.e., positive valence). Recent studies have drawn attention to the possibility that interactions between a service provider and a customer can also result in negative outcomes, where at least one of the actors experiences a decline in value from the interaction with the other actor (Plé & Chumpitaz Cáceres, 2010). This negative outcome has been conceptualized as co-destruction, defined as 'an interactional process between service systems that results in a decline in at least one of the systems' well-being (which, given the nature of a service system, can be individual or organizational)' (Plé & Chumpitaz Cáceres, 2010, p. 431). More specifically, value co-destruction can be experienced by any or all of the actors involved in an interaction and can be either intentional or accidental (Plé & Chumpitaz Cáceres, 2010). Value co-destruction implies that when an actor (for example, the customer) integrates a resource with another resource of another actor (for example, the service provider), the well-being of any one or both of these actors diminishes

(Plé & Chumpitaz Cáceres, 2010). This decline in well-being stems from a discrepancy between the actors' expectations regarding actual or perceived resource integration (Plé, 2017).

The extant literature generally encapsulates the factors that lead to a decline in well-being, and therefore co-destruction, under the term 'unexpected resource loss' (Smith, 2013, p. 1903). For example, a customer may interact with Alexa, Google Home, or Siri, expecting the experience to be frictionless. Instead they may find the actual experience to be frustrating and ineffective (Kaplan & Haenlein, 2018). In this case, the customer experiences a decline in well-being (frustration) and loses resources (time), thus experiencing value co-destruction by losing more than what was gained. Although the customer and the service provider can both cause resource loss, the extant literature has focused predominantly on resource loss that stems from the service provider's failure to fulfill its value proposition (Järvi et al., 2018). In this respect, the literature identifies a number of factors that can act as antecedents of resource loss and co-destruction, including absence of information (Järvi et al., 2018; Robertson et al., 2014), mistakes (Järvi et al., 2018), indifference, and technological failure (Zhang et al., 2018).

Several studies have identified resources that customers often lose when they interact with service providers (e.g., Plé, 2016; Smith, 2013). Although resource loss classifications differ among these studies, there is general consensus about the types of resources that can be lost during service interactions. A comprehensive resource framework is provided by Plé (2016), who identifies a number of resources that customers can lose as they interact with service providers, including economic, social, informational, emotional, temporal, and relational resources, as well as resources related to the customer's role, such as role clarity. The customer's role during service interactions has only recently been examined in the service literature, as studies have highlighted the importance of considering the detrimental effects of customer participation. Chowdhury et al. (2016) draw attention to the negative aspects resulting from co-creation and identify role conflicts and ambiguity, both of which can lead to tension. Blut et al. (2019) reveal that active customer participation can lead to role stress, including role conflict, role overload, and role ambiguity, and that such stress increases based on the task scope and the beneficiary participation.

Recent studies have also demonstrated a link between resource loss and resource deficiency and misintegration (e.g., Smith, 2013). Resource deficiency occurs when one or more of the actors do not possess the required operant resources (e.g., knowledge) to be used during the interaction. As a result, resource deficiency can have a compounded effect on how other resources are utilized during the interaction. If the customer is deficient in a particular resource (e.g., trust), a negative influence on the delivery of another resource (e.g., information) by the service provider may result (Vafeas et al., 2016). The actors involved in the encounter can also intentionally or unintentionally misintegrate their own resources or the resources of other actors during the interaction (Plé & Chumpitaz Cáceres, 2010). Resources are misintegrated when any of the actors fail to integrate their operant and operand resources in an 'appropriate or expected' manner from the other actor's perspective (Plé & Chumpitaz Cáceres, 2010, p. 432). Consistent with this view, Laud et al. (2019), propose an extensive typology of resource misintegration manifestations, which include deceptive integration of resources (deliberate concealment of resource integration), misunderstanding of how to integrate resources (failure to understand how to correctly integrate resources), negligent integration of resources (deliberate inattention in the integration of resources) and unwillingness to integrate resources (deliberate withholding or withdrawal of resources). As resource misintegration can manifest itself in different ways, uncovering the distinct antecedents of resource loss makes it possible to obtain early warning signs of co-destruction (Laud et al., 2019).

The negative impact of co-destruction can be so substantial that customers involved in a failed interaction may refuse to collaborate again in subsequent interactions (Prior & Marcos-Cuevas, 2016). Customers can also publicly manifest their feelings regarding the failed interaction with the service provider through negative word of mouth on social media, which can harm the service provider's image and reputation (Balaji et al., 2016).

A significant limitation of previous co-destruction studies is the research context. Whereas numerous studies have recently investigated co-destruction and its associated resource loss, most studies have focused on traditional, human-to-human interaction service settings (Smith, 2013), such as travel insurance (Blut et al., 2019) and B2B settings (Chowdhury et al., 2016; Vafeas et al., 2016). By contrast, little empirical research has explored co-destruction in relation to AI-powered technologies, which are permeating many service settings. For instance, while co-destruction has been explored in the context of physical (embodied) service robots in elderly settings (Čaić et al., 2018), there has been no exploration of co-destruction in the context of virtual (disembodied) service robots (Wirtz et al., 2018), such as AI-powered chatbots.

Virtual AI-driven service settings present a distinct context whereby (1) the FLE is replaced by a virtual and disembodied conversational agent that is trained to understand and, importantly, mimic human behavior (Holz et al., 2009), and (2) the customer is expected to be more involved and to perform some of the tasks that were previously performed by the FLE (Kaartemo & Helkkula, 2018).

AI technologies are introduced in service settings to support 'the co-creation of value between a service provider and customer at the organizational frontline' (Keyser et al., 2019,

p. 158). However, co-creation is not the only outcome of frontline interactions, and co-destruction remains an important possibility. It is therefore important to understand the reasons for, and the situations that lead to, co-destruction (Echeverri & Skålén, 2011; Plé & Chumpitaz Cáceres, 2010). Our study seeks to bridge this gap in the knowledge by exploring the antecedents of co-destruction and the resulting resource loss in AI-powered service environments.

Research Method

Since there is a dearth of empirical studies on this topic, we utilized an exploratory research design involving a qualitative research method to gain a rich understanding of how customers behave and interact with AI technologies, as well as to understand the process of co-destruction (Edmondson & McManus, 2007). We conducted in-depth semi-structured interviews with customers who had interacted with AI chatbots in a customer service context in the past, as these participants were considered to have the required expertise in this area. The implementation of AI-powered applications, such as chatbots, is predominantly concentrated in customer service environments in service-heavy industries, such as financial services, telecoms, retail, and travel (Kannan & Bernoff, 2019). A customer service setting, therefore, lent itself well to be explored within our study.

Data Collection

We developed an interview guide based on a review of earlier literature. We included questions related to the resources required during the interaction (Grönroos & Voima, 2013; Hilton & Hughes, 2013), sources of frustration (Echeverri & Skålén, 2011), resource loss (Plé, 2016; Smith, 2013), and resource deficiencies and misintegration (Plé & Chumpitaz Cáceres, 2010; Smith, 2013).

Research and current reports show that service robot and chatbot usage is strongest among the younger demographic (Ivanov et al., 2018; SmartAction, 2018; Tuzovic & Paluch, 2018). This implies that not all demographics were equally contributive to our study. Thus, typical case sampling, a type of purposive sampling strategy, was used to select those cases considered 'most typical, normal or representative of the group of cases under consideration' (Teddlie & Tashakkori, 2009, p. 176). Purposive sampling enabled the selection of specific information-rich cases that were closely related to the study's aim (Patton, 2002), which is consistent with past qualitative co-destruction studies that sought to draw on rich data from informants with comprehensive experience in particular practices (Echeverri & Skålén, 2011; Quach & Thaichon, 2017). Younger customers who had experience interacting with chatbots were considered most suitable for the exploration of co-destruction—because they represent a demographic that relies heavily on technology for their day-to-day interactions (Buhalis et al., 2019), and because this allowed the collection of in-depth data on co-destruction episodes from real, authentic, past experiences.

We employed a recruitment screener to qualify participants so as to ensure that the participants had experienced interactions with an AI-powered chatbot in a customer service context at least once in the 12 months preceding the study. Participants were asked to provide details about their past chatbot interactions, such as the name of the service provider offering the chatbot and the name of the chatbot (where relevant), to verify that an interaction with an AI chatbot (and not a human representative) in a customer service context did indeed occur.

We conducted 27 face-to-face interviews with voluntary participants residing in Malta—a multicultural setting that provided access to a diversity of otherwise difficult-to-reach participants. Data was collected between June and September 2019. The data collection process was concluded when additional interview data showed that theoretical saturation was reached (Glaser & Strauss, 2017). On average, each interview lasted around 41 minutes. After obtaining consent from the interviewees, we recorded and transcribed all the interviews.

The participants' ages ranged from 21 to 46 years, fitting the sought demographic profile. The participants had obtained a relatively high level of education (undergraduate degree or higher) and occupied middle to upper management positions. The participants generally enjoyed using modern technology daily, and perceived novel applications as having high utility, which is characteristic of their generation (Roberts, 2018; Stewart et al., 2017). Indeed, the interviewees reported using AI-powered chatbots in various contexts, the most common being Fintech (financial technologies), an industry whereby technology is comprehensively used to improve and automate the delivery of financial services (Belanche et al. 2019). The interviewees mentioned that they generally used Fintech applications for convenience and control in managing their accounts. A full list of interviewee characteristics is set out in Table 1.

Interviewee	Occupation	Gender	Age	Main Chatbot Interaction	Education Level
I1	Teacher	Female	24	Retail Support	Bachelor’s degree
I2	IT Solutions Architect	Female	24	Fintech Support	Master’s degree
I3	CRM Coordinator	Female	26	Investment Product Support	Bachelor’s degree
I4	Teacher	Female	28	Fintech Support	Master’s degree
I5	Manager	Female	29	Fintech Support	Master’s degree
I6	Business Owner	Female	34	Banking Support	Master’s degree
I7	HR Manager	Female	37	Fintech Support	Bachelor’s degree
I8	Marketing and Communications Manager	Female	37	IT Product/Service Support	Bachelor’s degree
I9	Business Owner	Female	38	Fintech Support	Bachelor’s degree
I10	Digital Marketing Specialist	Female	38	IT Product/Service Support	Secondary education
I11	Student	Male	21	Retail Support	Secondary education
I12	Student	Male	22	Fintech Support	Secondary education
I13	Marketing Executive	Male	23	Retail Support	Master’s degree
I14	Teacher	Male	25	Fintech Support	Bachelor’s degree
I15	Customer Engagement Manager	Male	25	Fintech Support	Bachelor’s degree
I16	Head of Tech	Male	29	Fintech Support	Bachelor’s degree
I17	Business Owner	Male	30	IT Product Support	Master’s degree
I18	Co-Founder	Male	32	Fintech Support	Bachelor’s degree
I19	Technology Solutions Adviser	Male	32	Fintech Support	Bachelor’s degree
I20	Finance Manager	Male	33	Fintech Support	Bachelor’s degree
I21	Software Engineer	Male	34	Investment Product Support	Master’s degree
I22	CRM Manager	Male	35	Banking Support	Bachelor’s degree
I23	Entrepreneur	Male	35	Fintech Support	Master’s degree
I24	Management Consultant	Male	35	Fintech Support	Master’s degree
I25	Head of SEO	Male	41	IT Product/Service Support	Bachelor’s degree
I26	Chief Business Development Officer	Male	44	IT Product/Service Support	Bachelor’s degree
I27	Head of Advisory Services	Male	46	Fintech Support	Master’s degree

Table 1 – List of Interviewees

Data Analysis

We uploaded our transcripts into an NVivo 12 project for coding and followed the systematic approach outlined by Gioia et al. (2013)—an approach that has been employed in previous co-destruction research (Järvi et al., 2018; Vafeas et al., 2016). This process required organization of the data into first-order codes, which were closely linked to existing terms offered by the interviewees so as to preserve the authenticity of their expressions. The next stage involved establishing connections between the first-order codes, leading to the emergence of second-order themes. This procedure involved several readings of verbatim transcripts and establishing connections between the emerging themes and the data set. Once a viable set of themes was established, the second-order themes were condensed further into second-order aggregate dimensions. This process ensured a strong foundation for building a data structure, while enriching the qualitative rigor of the study by clearly showing the development of the process, from the primary data to the theoretical constructs (Gioia et al., 2013).

Following Bazeley and Jackson (2019), we identified a rich transcript as being particularly suitable to start the coding process and to generate a preliminary list of first-order codes. When the preliminary coding was concluded, we looked for links between the second-order themes to classify them into more developed, aggregate dimensions. For example, ‘poor chat progress’ and ‘incorrect interpretation’ were combined into the aggregate dimension ‘cognition challenges.’ We adopted this process for the rest of the data.

This analytical process resulted in the emergence of five distinct aggregate dimensions, which are shown in Figure 1 and set out in more detail in the next section.

First Order Codes	Second Order Themes	Aggregate Dimensions
Customer is not informed that the interaction is with a chatbot Customer discovers they are interacting with a chatbot after being made to believe that the interaction is with a human representative	Lack of clarity about chatbot presence	Authenticity Issues
Customer does not notice that the interaction is with a chatbot	Failure to recognise chatbot	
Customer receives the same/similar answers to different questions Consistent chatbot repetition (looping) of questions/answers Chatbot asks too many questions to understand issue Deadlock in chat	Poor chat progress	Cognition Challenges
Chatbot does not understand or misunderstands query/problem Chatbot provides a reply that is out of context Customer does not phrase question correctly	Incorrect interpretation	
Customer perceives lack of human touch during conversation Chatbot does not comprehend the urgency of the situation Chatbot does not diffuse feelings of anger, frustration, stress and concern	Lack of empathy	Affective Issues
Chatbot does not relate to the situation Chatbot does not get involved in query/problem Chatbot does not personalise interaction Chatbot only provides standard/scripted replies	Lack of personalization	
Chatbot does not and cannot go the extra mile to solve query/problem Customer not acknowledged by chatbot for repeat interactions/loyalty	Insufficient effort	
Company only offers 'chatbot first, agent second' type of support Chatbot is made mandatory for customer support Customer cannot bypass chatbot in urgent situations	Forced interaction	
Chatbot is limited to answering simple, straightforward queries Chatbot does not accept pictures, emojis	Narrow scope	Functionality Issues
Chatbot provides very few options as a reply	Restricted options	
Information given to chatbot is not passed on to human representative Customer experiences a considerable difference between immediacy of chatbot and human representative response	Disjointed coordination between chatbot and human representative	Integration Conflicts
Customer does not believe that the chatbot can take the necessary action Customer does not believe that the chatbot is able to institute a follow up Chatbot does not build on or connect to previous conversations with the same customer	Lack of responsibility	
Chatbot does not automatically refer query to human agent during deadlock Chatbot does not provide an alternative (i.e. human) way of contacting company when query is not resolved	Lack of suitable human support back-up	
Customer cannot locate alternative contact details	No alternative human support	

Figure 1 – Data Analysis Framework

Findings

Our data analysis revealed that co-destruction in AI service settings emerges from five antecedents. These antecedents, in the order in which they occur during the interaction process, are authenticity issues, cognition challenges, affective issues, functionality issues, and integration conflicts. Any of these antecedents can lead to the perception of a failed service interaction and result in resource loss for customers and thus a decline in their well-being. Customers attribute responsibility for resource losses either to themselves or to the service provider and adopt avoidance or confrontative measures intent on regaining control over failed interactions. Table 2 sets out the five antecedents with their constituent concepts, the perceived customer resource loss, and the attributions for such resource loss.

Antecedent of resource loss	**Primary Customer Resource Loss**	**Customer Attribution of Resource Loss**		**Indicative Quote**
Authenticity Issues	Role Clarity	**Own**	Lack of resources to integrate	"I expect that I am told that it's a chatbot because then I would have to change the way I pose the question. So even your English, how you write a question, it has to be quite clear, for the chatbot to understand what you're actually asking." [I7]
		Service Provider	Deceptive integration of resources	"I'm a bit more wary today in the sense that I am on the lookout to see if it is a chatbot. They are hidden much better than before, and I do question myself, is this a chatbot or not?" [I27]
Cognition Challenges	Emotional	**Own**	Misunderstand-ing of how to integrate resources	"Even the language, how you speak it. If you make a mistake when you're typing, the chatbot might not recognize the word or it might not know what you're asking" [I1]
		Service Provider	Negligent integration of resources	"I believe that this [cognition challenges] depends on the company, to what extent it has fed the chatbot with input and information. But if it is the bare minimum, if the company has not invested enough money so that the robot is 100%, I don't imagine that the chatbot is able to answer most of my questions." [I4]
Affective Issues	Relational	**Own**	Lack of resources to integrate	"I realized that I was talking to a chatbot, but I didn't really notice honestly speaking whether I could talk to a human… I just kept getting the same answer." [I6]
		Service Provider	Unwillingness to integrate resources	"There is only so much interpersonal programming that can be done with a chatbot… in my case, the chatbot's insistence to help me got annoying, then trying to ask for help meant that it was at least an hour before somebody [a human representative] actually helped me...it wasn't a good experience." [I15]
Functionality Issues	Temporal	**Service Provider**	Lack of resources to integrate	"Developers should program… the bot to tell me listen you asked me this question and with 60% accuracy I can give you this answer, but it can be this or that… to let me know of its own limitations." [I16].
Integration Conflicts	Informational	**Own**	Lack of resources to integrate	"The conversation [with the chatbot] closed and I had to contact the company again because I didn't have my reply. Coming to think of it, I didn't even ask if I could speak to a human representative… I didn't try" [I10]

		Service Provider	Negligent integration of resources	There was a lot of to-ing and fro-ing, either I wasn't clear with what I needed, or the bot did not understand me, and I wanted to switch to a live chat [with a human]. Since we were in a deadlock, I expected the bot to do the transfer, or to tell me who I can contact, rather than me saying I want to speak to a live agent. [I26]

Table 2 – Customer Perceptions of Resource Loss and Attributions of Resource Loss

Authenticity Issues

Authenticity issues stem from the shrouded presence of a chatbot during an interaction, such as when a customer perceives that the service provider is intentionally hiding or covering up the identity of the chatbot. Participants mentioned that when the identity of the chatbot is not clear, they depend on a number of cues to determine whether they are interacting with a chatbot or a human agent. These cues include receiving instant replies to questions, noticing perfect punctuation and spelling, or repeatedly obtaining the same answers to different queries. Customers felt deceived when they were made to believe they were interacting with a human agent but found out that they were actually interacting with a chatbot.

This uncertainty affected customers' role clarity—that is, the extent to which they understood the role they must fulfill in the interaction. Customers were uncertain whether to change their style of communication, to write in a keyword-like manner, or to write in a different way. They did not know whether to be curt or friendly, and what stance to adopt to demonstrate that their issue was important.

> I expect that I am told that it's a chatbot because then I would have to change the way I pose the question. So even your English, how you write a question, it has to be quite clear for the chatbot to understand what you're actually asking. [I7]

Customers held themselves and the service provider equally accountable for the lack of role clarity that arises due to authenticity issues. Customers realized that they might not possess the skills that allow them to recognize that they are communicating with a chatbot. For example, participants remarked that although they are generally alert and attentive during their conversations, they might lack the ability to discern nuances that are specific to chatbot behavior. Additionally, participants discussed the service provider's deceptive integration of resources through the deliberate misrepresentation of a chatbot presence; for example, when the service provider intentionally opted not to disclose the chatbot identity or if the chatbot was purposely assigned human characteristics, such as being made to write imperfect text, this was labeled 'unfair' and 'dishonest.' Furthermore, service providers occasionally attribute human names to chatbots for increased levels of anthropomorphism (Araujo, 2018); thus, unless this is indicated explicitly during the chat, customers can easily mistake the chatbot for a human representative.

Cognition Challenges

The findings demonstrate that customers perceive a number of cognitive challenges with using chatbots. Chatbots exhibit a lack of understanding when the chat progress is poor, such as when they ask an excessive number of questions to comprehend an issue or they consistently provide the same answer to different customer questions. Cognitive challenges were also observed through instances of incorrect interpretation, such as when chatbots misunderstand a query or problem and provide an unrelated reply. One respondent complained that 'the reply that I received had nothing to do with my question—it was irrelevant—so it was evident that the chatbot did not understand my question' [I20].

The data showed that incomprehension breeds feelings of frustration and anger in customers. Although customers may not expect the chatbot to fully resolve their problems or issues, they do expect that, at a minimum, it is able to understand the context of their question and to provide adequate guidance. When this is not the case—for example, when the chat results in a deadlock—customers feel agitated and upset because they feel that they have lost control of the interaction. If customers are already upset and frustrated pre-interaction, their anger and frustration will only be exacerbated in cases characterized by a chatbot's lack of cognition.

Interestingly, participants were observed to attribute such emotional resource losses to both the service provider and themselves. The service provider was assigned responsibility for deliberate inattention during the creation and evolution of the chatbot—for instance, if the chatbot was not trained properly or not provided with the correct inputs. One participant remarked that functionality issues led him to believe that the chatbot 'needs more development at this point in time' [I19]. However, participants admitted that they also have a part to play in ensuring that the chatbot understands their request; they pointed to their own failure to understand how to correctly integrate resources when they did not adapt their communication skills (e.g., their writing style and use of keywords) to be better understood by the chatbot:

> The chatbot kept asking me, 'which is your account?', and I retyped the problem, and it gave me the same answer. And then at the end, I realized that my wording might not have been correct. As soon as I changed the wording, the chatbot immediately pointed me to the right answer. [I14]

Affective Issues

The data analysis showed that customers expect chatbots to exhibit a degree of empathy. In customer support situations, customers perceive chatbots as substituting human employees and, as a result, expect an element of sympathy and personalization within the interaction. One participant articulated that 'rather than just understanding what I'm typing, I want the chatbot to understand, to feel, what I'm feeling' [I05]. However, the participants generally believed that regardless of their level of technological advancement, chatbots are unable to adapt easily to customers' emotional state and to diffuse customers' feelings of anger, frustration, stress, and concern.

Consequently, customers experience relational resource losses when they determine that interactions with chatbots are devoid of affective understanding. They perceive regular interactions with human support agents as a way to develop a deeper bond with the service provider, which often involves building a relationship with particular employees who, in turn, may acknowledge the customer's repeat interactions. In contrast, chatbot interactions were described as 'clinical' [I16], leaving customers feeling unvalued and experiencing feelings of detachment from the service provider.

> I thought it [the chatbot] was rather impersonal... It made me feel distant from the company. I didn't like that. If it were my company, I would want my customers to feel comfortable and close to the company, not distant. [I04]

Participants attributed affective issues to the service provider's deliberate withholding of resources and information. Participants reasoned that they felt let down by the service provider when they were forced to interact with a chatbot rather than be given human support during critical, urgent situations—for example, when payment fails upon a hotel checkout, resulting in the customer potentially missing a flight as he waits for the payment transfer to be put into effect. In such cases, which are characterized by a high degree of anxiety and strong feelings of anger, customers expect to be met with a high level of empathy and reassurance. When customers are required to interact with a chatbot instead, attribution judgments towards the service provider are heightened. The service provider is perceived as withdrawing human resources (human FLEs) and, as a result, blamed for their unwillingness to integrate resources.

Customers also assume a minimal degree of responsibility for resources losses that occur as a result of affective issues. When the service provider adopts a 'chatbot first, agent second' policy, customers generally do have the option to speak to a human representative; however, they have to pass through the chatbot first and instruct the chatbot to transfer the conversation on to a human. However, not all customers are aware of this functionality and how to use it. Participants remarked how during urgent, emotional situations, they might lack the presence of mind to check or notice the option to transfer the conversation to a human representative.

Functionality Issues

Our findings revealed that customers perceive chatbots to be limited in their functionality. Despite being powered by AI, chatbots can only offer limited assistance during chat interactions. For example, customers perceive chatbots as a suitable replacement to humans when answering simple, straightforward questions; however, they cannot be relied on to solve more complex queries, as the scope of their abilities is generally narrow. The limited functionality of chatbots was also reflected in their inability to process non-textual inputs, such as pictures or emojis, which customers may prefer to use to express their feelings or preferences.

Despite expecting chatbots to be limited, customers do not expect significant resource losses as a result of such functional limitations. Yet, participants reported the loss of significant time resources when they needed to repeat a request or restart the entire conversation with a human. Such temporal losses are further attenuated, as they contrast heavily with customers' prior expectations of chatbot speed and agility.

> I'm not going to use the [company name] chatbot ever again, because it's a waste of time. Because if you use it with the intent to have an immediate reply, and then it turns out to be more complicated, then I would be more frustrated. [I04]

Participants attributed functionality issues completely to the service provider. Functionality issues are perceived to result from the unavailability of specific chatbot features, which is the responsibility of the service provider. More precisely, such attributions of misintegration were observed when the chatbot failed to set a customer's expectations—for example, by neglecting to inform the customer of limitations in its functionality, or by specifying the degree of accuracy in the given answers.

Integration Conflicts

Our analysis identified integration conflicts as another antecedent of resource loss. These conflicts arise from disconnects between the chatbot and other customer support channels, generally manned by human representatives. This can occur when, for example, information collected by the chatbot in the initial stages of the conversation is not conveyed to a human representative, or when the chatbot does not automatically transfer a complex or deadlocked conversation to a human representative.

Integration conflicts do not only result in temporal and emotional resources losses (time wastage and frustration); such conflicts also cause customers to experience informational losses. Customers perceive that chatbot conversations are not stored; as a result, they feel that they have lost their frame of reference relating to a specific problem or issue. In such cases, customers perceive that they have lost their ability to request an audit trail, including details of who they have spoken to and about what.

> In my case, the chatbot definitely did not keep any data, and I had to repeat it and start from scratch every time I logged in when I was speaking to a new chatbot, because this was over a period of months…there was zero traceability. [I08]

Participants blamed the service provider for informational losses occurring through such conflicts, although in some cases, the participants also assumed a degree of responsibility. Customers deem the service provider responsible in cases of poor organizational procedures, which inhibit a human representative from following up on previous conversations with chatbots. The service provider was also blamed for not including a clear exit option when interacting with a chatbot, thus enabling customers to shift their interaction to a human. Participants felt that this reflected deliberate inattention on the service provider’s part. Customers also pointed at their own limitations during chatbot conversations when they did not notice specific options, such as the possibility of saving the chat conversation (to counter informational losses), or the possibility of transferring the conversation to a human representative.

Customer Reactions to Resource Losses

We also observed that resource loss influences customer emotions and subsequent behaviors to different degrees. Milder reactions may involve an immediate call for human support through other channels, such as phone or email, or refusal to reuse the chatbot, especially if the negative interaction was one in a series of negative experiences.

Situations in which participants experienced deeper emotional resource losses led to harsher reactions. A common reaction involved terminating a service with the service provider or moving to a competitor, especially in cases of a new service where the customer had not yet invested significant time and effort in developing a relationship with the service provider.

> I was like, you know what? I'm okay, I don't have the problem anymore, because I'm stopping the service straight away. I'm fed up. [I25]

The harshest reactions involved propagating negative word of mouth on social media. Although negative word of mouth was not as common as the other reactions identified, we observed it to be spurred by continuous negative service from the chatbot, such as looping or failing to understand the customer's query.

> Basically, it [the chatbot] got me nowhere…it was extremely frustrating. I think in all it took me a good three months to get it sorted out. I had to actually get it to Twitter, complaining live on Twitter to get someone to speak to me. [I08]

Resource loss activates customers' desire to take control of a situation by hurting or getting even with the service provider. This behavior may imply a coping strategy, whereby customers select a specific, and generally negative, course of action in an attempt to restore their own well-being (Mick & Fournier, 1998). Avoidance and confrontative coping behaviors were evident when customers attempted to restore their well-being in AI-powered service interactions. Attempts to call for human support and refusal to reuse the chatbot are examples of 'avoidance' coping strategies, where customers attempt to distance themselves from new technology. On the other hand, termination of service, switching to a competitor, and engaging in negative word of mouth demonstrate 'confrontative' coping strategies.

Discussion and Theoretical Contributions

We investigated the process of co-destruction during customer interactions with AI-powered chatbots. In doing so, we aimed to address two distinct goals: first, to understand the transformational effects of AI on co-destruction, and second, to analyze the process of co-destruction from the customer perspective. The findings from this empirical study contribute to the current understanding of co-destruction in three ways.

First, we demonstrated that co-destruction is a process that is set into motion by a number of factors (antecedents), resulting in a decline in well-being for at least one of the actors—in this case, the customer. A decline in well-being comprises resource loss. In order to counter such resource loss, customers undergo an exercise of responsibility attribution to determine who was responsible for the resource loss and decide what action to take. This process allows customers to perceive that they have re-gained a degree of control over the encounter. A conceptualization of co-destruction based on this process is set out in Figure 2.

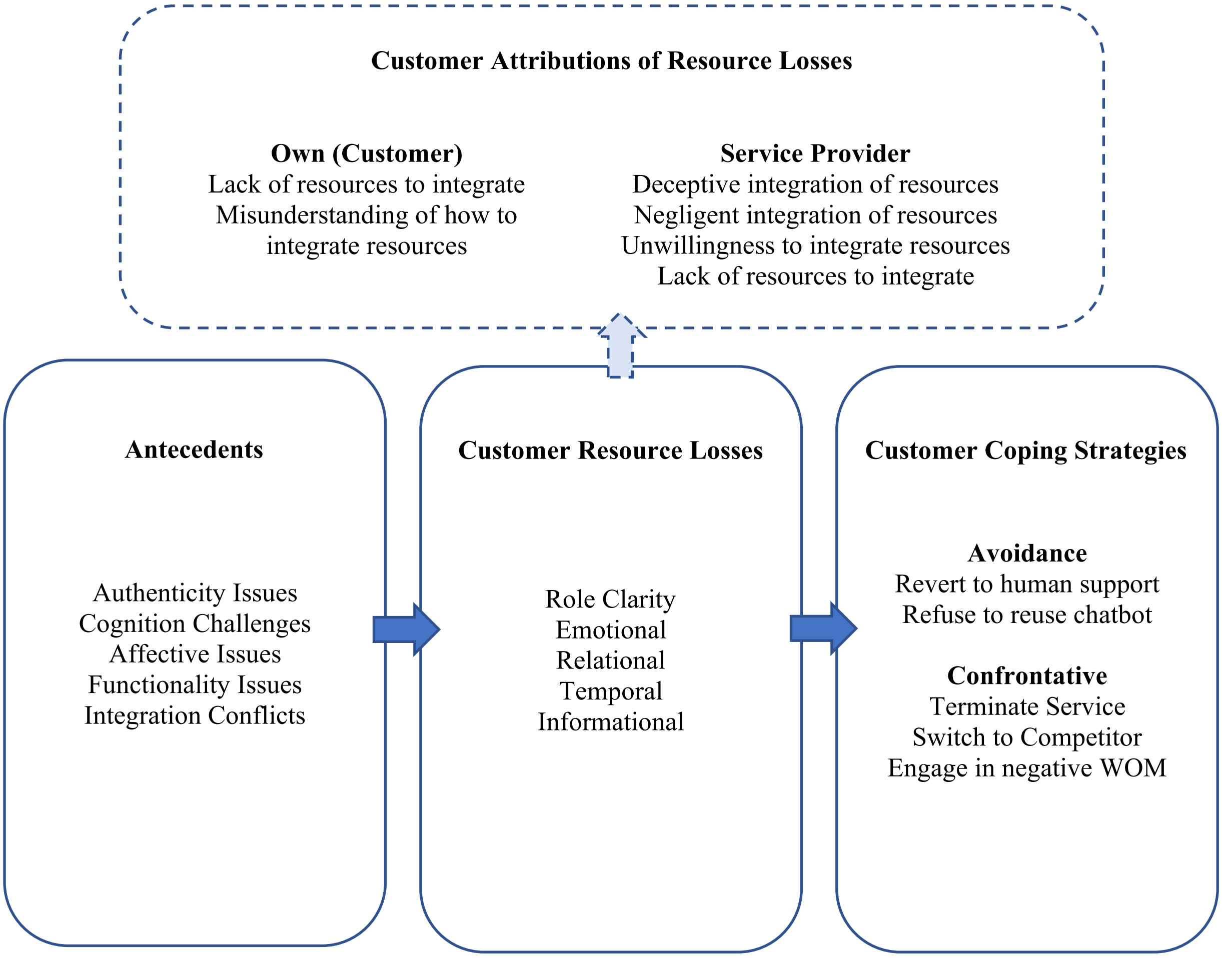

Figure 2 – A Model of Co-Destruction Through AI-Powered Technologies

Whereas previous studies have contributed models of co-creation from the customer perspective (Etgar, 2008; Füller, 2010), our study addresses the gap in the literature by proposing a model of co-destruction from the customer's viewpoint. Our model provides a richer conceptualization of the link between customer resource loss, attributions of resource loss, and customer coping strategies following such loss. As previous co-destruction studies tended to investigate resource loss, attributions of resource loss, and coping strategies separately, our study makes a noteworthy contribution to the extant understanding of value co-destruction as a complete process, which has been largely overlooked in previous literature (Ostrom et al., 2015).

Second, our study empirically demonstrated the transformational role of AI in value co-destruction. Our conceptualization showed that while a number of antecedents of resource loss are common to a multitude of service settings, AI-powered service settings are affected by a number of specific antecedents, necessitating their own investigation.

Three of the identified antecedents—cognition challenges, functionality issues, and integration conflicts—are consistent with previous studies that examined co-destruction through interaction with physical robots or in human-to-human B2B settings (Čaić et al., 2018; Järvi et al., 2018; Vafeas et al., 2016). Our findings suggest that cognition challenges stem from the lack of understanding of AI technology and echo previous studies suggesting a lack of understanding as an antecedent of resource loss (Čaić et al., 2018; Järvi et al., 2018; Vafeas et al., 2016). The identification of functionality issues as a reason for co-destruction corroborates previous studies that outline the inability to serve as a key antecedent of co-destruction (Järvi et al., 2018). This notion is congruent with the idea that co-destruction occurs when an operant resource by one of the actors (the AI technology offered by the service provider) is deemed to be inadequate and cannot meet customer requests satisfactorily (Echeverri & Skålén, 2011). Integration conflicts are related to inadequate coordination, which was previously proposed as an antecedent of co-destruction, albeit in B2B settings (Vafeas et al., 2016). However, whereas previous studies consider inadequate coordination to arise from the lack of alignment between two actors or systems (Vafeas et al., 2016), our findings suggest that poor organizational configurations of one actor (the service provider) cause such misalignment. The infusion of AI into service thus renders value creation a more complex process whereby coordinated, harmonized resource inputs assume even greater importance.

Two of the identified reasons for resource loss, affective and authenticity issues, are specific to AI-powered environments. Both of these, however, have not been identified in the extant co-destruction literature.

Chatbots, even if powered by AI, are unlikely to be autonomous and to express genuine emotions (Robinson et al., 2020). They may be trained to mimic human responses and express basic emotions, which may be suitable or even ideal in low-involvement, mundane chatbot encounters (e.g., in questions regarding package delivery status). However, in high-involvement encounters (e.g., refund problems), when customers expect empathy and understanding (Rafaeli et al., 2017), they may be disappointed with chatbot expressed emotions, especially if they interpret such emotions as superficial or insincere. In such instances, the opportunity for successful collaboration between the customers and the service provider (co-creation) is not only lost, but it also becomes counterproductive, as customers perceive a decline in their relational well-being as a result of the interaction. It is also evident that in these cases, co-destruction emerges from the disconnect between chatbot ability and task type. As opposed to rule-based chatbots, AI-powered chatbots have the ability to learn from past interactions, which may lead to their premature deployment in situations that require not only mechanical or analytical intelligence, but also intuitive and empathetic intelligence (Huang & Rust, 2018). These co-destruction possibilities are further exacerbated when chatbot use is imposed or when there is a lack of clear communication on how to converse with a human representative, as the customer perceives a loss of control and freedom over the situation.

As advances in NLP and ML lead to more humanlike chatbot conversations (Wirtz et al., 2018), it is becoming increasingly common for customers to be unaware that they are interacting with a chatbot. Recent literature classifies instances where one actor is unaware that the other actor is not human as ‘counterfeit service encounters’ (Robinson et al., 2020, p. 367). Our findings show how, similar to counterfeit goods (Eisend & Schuchert-Güler, 2006), counterfeit service encounters initiate a process of co-destruction, as customers feel deceived and are unable to retain full control over the conversation. These results imply that the process of co-destruction is rendered more complex in service environments characterized by AI due to the perception of multiple FLE identities (human vs. ‘counterfeit human’).

While lack of clarity about the identity of the FLE causes a customer to lose role clarity, it can also spur further resource losses for not only the customer, but also the service provider. Consistent with Smith (2013), our study shows the existence of ‘loss cycles’ or ‘downward spirals’ pertaining to secondary resource losses that occur when customers attempt to regain lost resources but instead incur additional resource losses. However, we supplement Smith’s (2013) findings by proposing that, in the context of AI-powered service interactions, these downward spirals or loss cycles can be extended to include resource losses incurred by the service provider. When customers lose role clarity, they are not aware of the new role that they need to assume, that of speaking to the chatbot in a ‘keyword-like,’ systematic manner. This behavior results in resource losses for the service provider, as it limits the extent to which the chatbot can learn from customer interactions. In AI-powered service environments, which necessitate correct and consistent data inputs for systematic and autonomous system learning, the lack of such data input means that the AI application is not able to learn effectively, and the interaction degenerates over time.

Third, we offer a significant contribution to the extant, yet limited, literature on the customer perspective of value co-destruction. While the benefits of AI technology adoption are clear for service providers, it is important to obtain a customer-centric view on the implementation of AI technologies at the frontline and to understand the factors that might lead the customer to experience co-destruction and when. This understanding is especially important given the crucial role of customers in AI-powered service interactions, when the customer is at the very core of the service delivery (Kaartemo & Helkkula, 2018).

Customers do not expect reduced well-being to be an outcome when they engage in chatbot conversations. When resource loss occurs, customers resolve to resume control of the situation by first attributing responsibility for the resource loss and then adopting a coping strategy. Our findings suggest that customers largely attribute their resource losses to resource misintegration by the service provider (Table 2). Resource misintegration is perceived as an intentional action by service providers to maximize benefits for themselves.

Customers only attribute themselves with resource deficiency or resource misintegration in a limited number of cases. Such an attribution is the case when customers do not believe they have the required capabilities to recognize chatbot presence (self-efficacy), and when they do not adapt their communication style to one that can be more easily understood by the chatbot. This tendency of customers to attribute resource loss to the service provider can be explained by the self-serving bias, which states that in the case of a service failure, customers are more likely to ascribe failure to third parties (Bendapudi & Leone, 2003). Previous research on the self-serving bias suggests that this bias can be reduced when customers are given a choice of whether to participate in service production or otherwise (Bendapudi & Leone, 2003). It follows that cases of imposed chatbot use, which do not grant the customer any choice, exacerbate the self-serving bias and result in a higher level of resource loss attributed to the service provider. Indeed, customers clearly demarcate instances of resource loss that stem from imposed chatbot use as deliberate unwillingness to integrate resources by the service provider.

Our study demonstrates that for the customer, the co-destruction process extends beyond immediate resource loss and evolves into making attributions for that loss and taking corresponding avoidance or confrontative measures aimed at the service provider. This finding validates the importance of extending the co-destruction literature to the field of attribution of responsibility in order to expand the limited knowledge on the consequences of co-destruction and the array of emotional coping strategies that consumers may display in response to resource loss (Tsarenko et al., 2019).

Practical Implications

Our findings suggest a number of strategic implications for managers and practitioners in service sectors.

AI technologies on the frontline have been created specifically to encourage co-creation between the service provider and the customer. However, our observations demonstrate that co-destruction is also possible. Co-destruction emerges when the co-created service fails to meet customers' expectations. It is important for managers to realize that when AI applications, such as chatbots, are introduced to the frontline, customers view such applications as a substitute for human FLEs. As a result, customers hold similar, if not completely identical, expectations regarding service levels. In light of this, it is important for service providers to help customers understand any limitations inherent in the AI application and to ensure that the chatbot explains the process to adopt when faced with such limitations so as to avoid customer resource loss. More precisely, it is important for service providers to understand that customer queries can vary significantly in their degree of complexity and involvement. While AI chatbots can easily tackle simpler queries, problems arise when they face more complex questions. Service providers should first ensure that the question’s degree of complexity is identified as soon as possible, and then offer, if the question is determined to be complex, a clear and seamless chat transfer to a human support representative as early on in the process as possible.

Although chatbot disclosure at the start of an interaction may negatively prejudice customers against the effectiveness of such chatbots (Luo et al., 2019), our findings convey the negative impact of perceived deception by service providers. Customers are also becoming increasingly vigilant in determining the identity of the FLE, and may erroneously judge a human FLE to be a chatbot, or vice versa, when the FLE identity is not disclosed. Service providers are therefore encouraged to clearly advise customers of the identity of the FLE to avoid feelings of deception and distrust. Such a notification can be offered at the start of the interaction or even at the end (Belanche et al., 2020). Furthermore, disclosing the presence of a chatbot may be regulated or considered standard practice in the near future, in light of ethical concerns (Robinson et al., 2020).

Furthermore, we demonstrated that when customer interactions with AI chatbots are negative, resulting in customer resource loss, such experiences can have serious negative ramifications on service providers, as customers can opt for more costly customer support channels, such as a phone channel. In such cases, an investment in AI technology intended to result in cost savings, might backfire and result in a heavier load on other support channels. When customer resource loss is significant, customers may opt for harsher action, such as terminating the service, switching to a competitor, or complaining on social media. The possibility of such behaviors also has a number of implications in terms of how the success of chatbot applications is measured. Besides cost savings and insight gain, it is important for service providers to adopt a customer-centric view and obtain a clear understanding in terms of what chatbot success looks like from the customer perspective.

Limitations and Future Research

Utilizing a qualitative approach enabled us to undertake an in-depth exploration of a distinct phenomenon, value co-destruction, in a novel context, AI-powered service interactions. Like other qualitative studies, such an approach limits the generalizability of our study, as our findings cannot be projected to an entire population of human-AI interactions in a statistical sense. More importantly, despite the fact that our study is related to a growing economy that is becoming increasingly reliant on technology and involves an increasingly multicultural workforce (and population), we believe that our findings convey an emerging phenomenon that cannot yet be generalized to other contexts in similar service industries across the globe.

Our study did not evaluate factors relating to consumers' cultural behavior. Culture can influence customer attitudes and behaviors in service settings (Chan et al., 2010); thus, this would be a fruitful area for further work. Future research could analyze whether perceptions of value loss, loss attributions, and coping strategies differ based on customers' cultural value orientations. These insights can contribute to a more developed understanding of the process of co-destruction in AI-driven service encounters.

Quantifying the strength of the customers' feelings and the prevalence of the perceived resource loss was outside the scope of this study. Future research could build on our study to develop a scale that can measure and quantify the extent of identified resource losses. Such research could link measurement indictors to the concept of resource loss and provide a systematic manner in which to measure and evaluate resource loss linked to co-destruction. A focus on the different ways that resource loss could be countered, or at least minimized, would also be useful to advance knowledge on the subject and especially to provide practical managerial guidelines in terms of remedial or recovery strategies that can be adopted in cases of value co-destruction.

Further work is also required to validate the identified resource losses in additional AI settings—for example, those provided by voice-controlled digital assistants, such as Alexa. Additional empirical approaches, such as lab or field experiments, could be adopted to allow for a more in-depth exploration of this topic.

Lastly, additional research is needed to ascertain the impact of resource misintegration and deficiency in AI settings. AI applications, such as chatbots, are smart and have the ability to learn from every interaction they have (Kumar et al., 2016). Thus, it is important to examine how resource misintegration and deficiency by the customer or service provider at the start of the interaction could have a compounded effect and cause further resource loss by the end of the interaction.

Acknowledgements

The authors gratefully acknowledge the interviewees who participated in this study, as well as the reviewers and the attendees who provided feedback during the AIRSI 2019 conference: Artificial Intelligence and Robotics in Service Interactions.

Declaration of Interest

No potential conflict of interest was reported by the authors.

References

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, *85*, 183–189.

Balaji, M. S., Khong, K. W., & Chong, A. Y. L. (2016). Determinants of negative word-of-mouth communication using social networking sites. *Information and Management*, *53*(4), 528–540.

Bazeley, P., & Jackson, K. (2019). *Qualitative data analysis with NVivo* (3rd ed.). SAGE Publications Ltd.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management and Data Systems*, *119*(7), 1411–1430.

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal*, *40*(3–4), 203–225.

Bendapudi, N., & Leone, R. P. (2003). Psychological Implications of Customer Participation in Co-production. *Journal of Marketing*, *67*(1), 14–28.

Bitner, M. J., Faranda, W. T., Hubbert, A. R., & Zeithaml, V. A. (1997). Customer contributions and roles in service delivery. *International Journal of Service Industry Management*, *8*(3), 193–205.

Blut, M., Heirati, N., & Schoefer, K. (2019). The Dark Side of Customer Participation : When Customer Participation in Service Co-Development Leads to Role Stress. *Journal of Service Research*.

Bock, D. E., Wolter, J. S., & Ferrell, O. C. (2020). Artificial intelligence: disrupting what we know about services. *Journal of Services Marketing*, *ahead-of-print*.

Buhalis, D., & Cheng, E. S. Y. (2020). Exploring the Use of Chatbots in Hotels:Technology Providers'Perspective. In *Information and Communication Technologies in Tourism 2020* (pp. 231–242). Springer International Publishing.

Buhalis, D., Harwood, T., Bogicevic, V., Viglia, G., Beldona, S., & Hofacker, C. (2019). Technological disruptions in services: lessons from tourism and hospitality. *Journal of Service Management*, *30*(4), 484–506.

Buhalis, D., & Sinarta, Y. (2019). Real-time co-creation and nowness service: lessons from tourism and hospitality. *Journal of Travel and Tourism Marketing*, *36*(5), 563–582.

Čaić, M., Odekerken-Schroder, G., & Mahr, D. (2018). Service robots: Value co-creation and co-destruction in elderly care networks. *Journal of Service Management*, *29*(2), 178–205.

Camilleri, J., & Neuhofer, B. (2017). Value co-creation and co-destruction in the Airbnb sharing economy. *International Journal of Contemporary Hospitality Management*, *29*(9), 2322–2340.

Chan, K. W., Yim, C. K. (Bennett), & Lam, S. S. . (2010). Is Customer Participation in Value Creation a Double-Edged Sword? Evidence from Professional Financial Services Across Cultures. *Journal of Marketing*, *74*(3), 48–64.

Chandler, J. D., & Lusch, R. F. (2015). Service systems: A broadened framework and research agenda on value propositions, engagement, and service experience. *Journal of Service Research*, *18*(1), 6–22.

Chowdhury, I. N., Gruber, T., & Zolkiewski, J. (2016). Every cloud has a silver lining - Exploring the dark side of value co-creation in B2B service networks. *Industrial Marketing Management*, *55*, 97–109.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *October*, 1–9.

Ciechanowski, L., Przegalinska, A., Magnuski, M., & Gloor, P. (2019). In the shades of the uncanny valley: An experimental study of human–chatbot interaction. *Future Generation Computer Systems*, *92*, 539–548.

Cova, B., & Dalli, D. (2009). Working consumers: The next step in marketing theory? *Marketing Theory*, *9*(3), 315–339.

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*.

Demoulin, N., & Willems, K. (2019). Servicescape irritants and customer satisfaction: The moderating role of shopping motives and involvement. *Journal of Business Research*, *104*(December 2017), 295–306.

Echeverri, P., & Skålén, P. (2011). Co-creation and co-destruction: A practice-theory based study of interactive value formation. *Marketing Theory*, *11*(3), 351–373.

Edmondson, A., & McManus, S. (2007). Methodological fit in field research. *Academy of Management Review*, *32*(4), 1155–1179.

Eisend, M., & Schuchert-güler, P. (2006). Explaining Counterfeit Purchases : A Review and Preview. *Academy of Marketing Science Review*, *2006*(12).

Etgar, M. (2008). A descriptive model of the consumer co-production process. *Journal of the Academy of Marketing Science*, *36*(1), 97–108.

Füller, J. (2010). Refining Virtual Co-Creation from a Consumer Perspective. *California Management Review*, *52*(2), 98–122.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, *16*(1), 15–31.

Glaser, B. G., & Strauss, A. L. (2017). *The discovery of grounded theory: Strategies for qualitative research*. Routledge.

Gnewuch, U., Morana, S., & Maedche, A. (2018). Towards Designing Cooperative and Social Conversational Agents for Customer Service. *ICIS 2017: Transforming Society with Digital Innovation*, 0–13.

Griol, D., Carbó, J., & Molina, J. M. (2013). An automatic dialog simulation technique to develop and evaluate interactive conversational agents. *Applied Artificial Intelligence*, *27*(9), 759–780.

Grönroos, C., & Voima, P. (2013). Critical service logic: Making sense of value creation and co-creation. *Journal of the Academy of Marketing Science*, *41*(2), 133–150.

Harrison, T., & Waite, K. (2015). Impact of co-production on consumer perception of empowerment. *The Service Industries Journal*, *35*(10), 502–520.

Hilton, T., & Hughes, T. (2013). Co-production and self-service: The application of Service-Dominant Logic. *Journal of Marketing Management*, *29*(7–8), 861–881.

Ho, S.-H., & Ko, Y.-Y. (2008). Effects of self-service technology on customer value and customer readiness: The case of internet banking. *Internet Research*, *18*(4), 427–446.

Holz, T., Dragone, M., & O'Hare, G. M. P. (2009). Where robots and virtual agents meet: A survey of social interaction research across milgram's reality-virtuality continuum. *International Journal of Social Robotics*, *1*(1), 83–93.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172.

IDC. (2019). *Worldwide Spending on Artificial Intelligence Systems Will Grow to Nearly $35.8 Billion in 2019, According to New IDC Spending Guide*. International Data Corporation. https://www.idc.com/getdoc.jsp?containerId=prUS44911419

Ivanov, S., & Webster, C. (2019). Economic Fundamentals of the Use of Robots, Artificial Intelligence, and Service Automation in Travel, Tourism, and Hospitality. In *Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality* (pp.

39–55).

Ivanov, S., Webster, C., & Garenko, A. (2018). Young Russian adults' attitudes towards the potential use of robots in hotels. *Technology in Society*, *55*(December 2017), 24–32.

Järvi, H., Kähkönen, A. K., & Torvinen, H. (2018). When value co-creation fails: Reasons that lead to value co-destruction. *Scandinavian Journal of Management*, *34*(1), 63–77.

Kaartemo, V., & 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*, *4*(2), 1–18.

Kannan, P. V., & Bernoff, J. (2019). *Does your company really need a chatbot?* Harvard Business Review. https://hbr.org/2019/05/does-your-company-really-need-a-chatbot

Kaplan, A., & Haenlein, M. (2018). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25.

Kelleher, C., & Peppard, J. (2011). Consumer Experience of Value Creation - a Phenomenological Perspective. In A. Bradshaw, C. Hackley, P. Maclaran, & M. Duluth (Eds.), *European Advances in Consumer Research* (Vol. 9, pp. 325–332). Association for Consumer Research.

Keyser, A. De, Köcher, S., Alkire, L., Verbeeck, C., & Kandampully, J. (2019). Frontline service technology infusion: Conceptual archetypes and future research directions. *Journal of Service Management*, *30*(1), 156–183.

Kim, K., Byon, K., & Baek, W. (2019). Customer-to-customer value co-creation and co-destruction in sporting events. *The Service Industries Journal*.

Kumar, V., Dixit, A., Javalgi, R. (Raj) G., & Dass, M. (2016). Research framework, strategies, and applications of Intelligent Agent Technologies (IATs) in Marketing. *Journal of the Academy of Marketing Science*, *44*(1), 24–45.

Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., Wünderlich, N. V., & De Keyser, A. (2017). “Service Encounter 2.0”: An investigation into the roles of technology, employees and customers. *Journal of Business Research*, *79*, 238–246.

Laud, G., Bove, L., Ranaweera, C., Leo, W. W. C., Sweeney, J., & Smith, S. (2019). Value co-destruction: a typology of resource misintegration manifestations. *Journal of Services Marketing*, *January*.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases. *Marketing Science*, *December*.

Marinova, D., de Ruyter, K., Huang, M.-H., Meuter, M. L., & Challagalla, G. (2017). Getting smart: Learning from technology-empowered frontline interactions. *Journal of Service Research*, *20*(1), 29–42.

Mende, M., Scott, M. L., Bitner, M. J., & Ostrom, A. L. (2017). Activating consumers for better service coproduction outcomes through eustress: The interplay of firm-assigned workload, service literacy, and organizational support. *Journal of Public Policy and Marketing*, *36*(1), 137–155.

Mick, D. G., & Fournier, S. (1998). Paradoxes of technology: Consumer cognizance, emotions, and coping strategies. *Journal of Consumer Research*, *25*(2), 123–143.

Morosan, C., & DeFranco, A. (2016). Co-creating value in hotels using mobile devices: A conceptual model with empirical validation. *International Journal of Hospitality Management*, *52*, 131–142.

Oram, R. (2019). *Meeting Edward: Chatbots and the Changing the Face of the Hotel Guest Experience*. Oracle Hospitality Check-In. https://blogs.oracle.com/hospitality/chatbots-and-the-changing-the-face-of-the-hotel-guest-experience

Ostrom, A. L., Parasuraman, A., Bowen, D. E., Patrício, L., & Voss, C. A. (2015). Service research priorities in a rapidly changing context. *Journal of Service Research*, *18*(2), 127–159.

Patton, M. Q. (2002). *Qualitative research and evaluation methods: Integrating theory and practice*. Thousand Oakes.

Plé, L. (2016). Studying customers' resource integration by service employees in interactional value co-creation. *Journal of Services Marketing*, *30*(2), 152–164.

Plé, L. (2017). Why do we need research on value co-destruction? *Journal of Creating Value*, *3*(2), 162–169.

Plé, L., & Chumpitaz Cáceres, R. (2010). Not always co-creation: Introducing interactional co-destruction of value in Service-dominant Logic. *Journal of Services Marketing*, *24*(6), 430–437.

Prior, D. D., & Marcos-Cuevas, J. (2016). Value co-destruction in interfirm relationships: The impact of actor engagement styles. *Marketing Theory*, *16*(4), 533–552.

Quach, S., & Thaichon, P. (2017). From connoisseur luxury to mass luxury: Value co-creation and co-destruction in the online environment. *Journal of Business Research*, *81*(May), 163–172.

Rafaeli, A., Altman, D., Gremler, D. D., Huang, M.-H., Grewal, D., Iyer, B., Parasuraman, A., & de Ruyter, K. (2017). The Future of Frontline Research. *Journal of Service Research*, *20*(1), 91–99.

Ramaswamy, V., & Ozcan, K. (2018). What is co-creation? An interactional creation framework and its implications for value creation. *Journal of Business Research*, *84*(September 2016), 196–205.

Roberts, D. (2018). *Why generational attitudes toward technology matter | EY - Global*. EY. https://www.ey.com/en_gl/health/why-generational-attitudes-toward-technology-matter

Robertson, N., Polonsky, M., & McQuilken, L. (2014). Are my symptoms serious Dr Google?

A resource-based typology of value co-destruction in online self-diagnosis. *Australasian Marketing Journal*, *22*(3), 246–256.

Robinson, S. G., Orsingher, C., Alkire, L., Keyser, A. De, Giebelhausen, M., Papamichail, K. N., Shams, P., & Sobhy, M. (2020). Frontline encounters of the AI kind : An evolved service encounter framework. *Journal of Business Research*, *116*, 366–376.

SmartAction. (2018). *How demographics affect chatbot usage*. https://www.smartaction.ai/blog/demographics-affect-chatbot-adoption-use/

Smith, A. M. (2013). The value co-destruction process: A customer resource perspective. *European Journal of Marketing*, *47*(11/12), 1889–1909.

Stewart, J. S., Goad, E., & Cravens, K. S. (2017). Managing millennials : Embracing generational differences. *Business Horizons*, *60*(1), 45–54.

Syam, N., & 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*, *69*(January), 135–146.

Teddlie, C., & Tashakkori, A. (2009). *Foundations of mixed methods research*. SAGE.

Tsarenko, Y., Strizhakova, Y., & Otnes, C. C. (2019). Reclaiming the Future: Understanding Customer Forgiveness of Service Transgressions. *Journal of Service Research*, *22*(2),

Tussyadiah, I. P. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research*, *81*(February), 102883.

Tuzovic, S., & Paluch, S. (2018). Conversational Commerce – A New Era for Service Business Development. In M. Bruhn & H. K. (Eds.), *Service Business Development* (pp. 82–101). Springer Gabler.

Ukpabi, D. C., Aslam, B., & Karjaluoto, H. (2019). Chatbot Adoption in Tourism Services: A Conceptual Exploration. In *Robots, Artificial Intelligence, and Service Automation in*

Travel, Tourism and Hospitality (pp. 105–121).

Vafeas, M., Hughes, T., & Hilton, T. (2016). Antecedents to value diminution: A dyadic perspective. *Marketing Theory*, *16*(4), 469–491.

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research*, *20*(1), 43–58.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for Marketing. *Journal of Marketing*, *68*(1), 1–17.

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science*, *36*(1), 1–10.

Verleye, K. (2015). The co-creation experience from the customer perspective: Its measurement and determinants. *Journal of Service Management*, *26*(2), 321–342.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, *29*(5), 907–931.

Xu, A., Liu, Z., Guo, Y., Sinha, V., & Akkiraju, R. (2017). A New Chatbot for Customer Service on Social Media. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 3506–3510.

Yin, J., Qian, L., & Shen, J. (2019). From value co-creation to value co-destruction? The case of dockless bike sharing in China. *Transportation Research Part D: Transport and Environment*, *71*(June 2018), 169–185.

Zhang, T., Lu, C., Torres, E., & Chen, P.-J. (2018). Engaging customers in value co-creation or co-destruction online. *Journal of Services Marketing*, *32*(1), 57–69.