

# Kent Academic Repository

## Full text document (pdf)

### Citation for published version

Robinson, Stacey and Orsingher, Chiara and Alkire, Linda and De Keyser, Arne and Giebelhausen, Michael and Papamichail, K. Nadia and Shams, Poja and Temerak, M.S. (2019) Frontline encounters of the AI kind: An evolved service encounter framework. *Journal of Business Research*. ISSN 0148-2963. (In press)

### DOI

<https://doi.org/10.1016/j.jbusres.2019.08.038>

### Link to record in KAR

<https://kar.kent.ac.uk/77834/>

### Document Version

Author's Accepted Manuscript

#### Copyright & reuse

Content in the Kent Academic Repository is made available for research purposes. Unless otherwise stated all content is protected by copyright and in the absence of an open licence (eg Creative Commons), permissions for further reuse of content should be sought from the publisher, author or other copyright holder.

#### Versions of research

The version in the Kent Academic Repository may differ from the final published version.

Users are advised to check <http://kar.kent.ac.uk> for the status of the paper. **Users should always cite the published version of record.**

#### Enquiries

For any further enquiries regarding the licence status of this document, please contact:

[researchsupport@kent.ac.uk](mailto:researchsupport@kent.ac.uk)

If you believe this document infringes copyright then please contact the KAR admin team with the take-down information provided at <http://kar.kent.ac.uk/contact.html>



ELSEVIER

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: [www.elsevier.com/locate/jbusres](http://www.elsevier.com/locate/jbusres)

## Frontline encounters of the AI kind: An evolved service encounter framework

Stacey Robinson<sup>a,\*</sup>, Chiara Orsingher<sup>b</sup>, Linda Alkire<sup>c</sup>, Arne De Keyser<sup>d</sup>, Michael Giebelhausen<sup>e</sup>, K. Nadia Papamichail<sup>f</sup>, Poja Shams<sup>g</sup>, Mohamed Sobhy Temerak<sup>h,i</sup>

<sup>a</sup> Culverhouse College of Business, University of Alabama, United States of America

<sup>b</sup> Department of Management, University of Bologna, Italy

<sup>c</sup> Texas State University, United States of America

<sup>d</sup> EDHEC Business School, France

<sup>e</sup> Clemson University, United States of America

<sup>f</sup> Alliance Manchester Business School, The University of Manchester, United Kingdom

<sup>g</sup> Karlstad Business School, Sweden

<sup>h</sup> Cairo University, Egypt

<sup>i</sup> Kent Business School, University of Kent, Medway ME4 4TE, United Kingdom

### ARTICLE INFO

#### Keywords:

Service encounter  
Artificial intelligence (AI)  
Technology  
Customer experience  
Frontline employee  
Counterfeit

### ABSTRACT

Artificial intelligence (AI) is radically transforming frontline service encounters, with AI increasingly playing the role of employee or customer. Programmed to speak or write like a human, AI is poised to usher in a frontline service revolution. No longer will frontline encounters between customer and employee be simply human-to-human; rather, researchers must consider an evolved paradigm where each actor could be either human or AI. Further complicating this 2 × 2 framework is whether the human, either customer or employee, recognizes when they are interacting with a non-human exchange partner. Accordingly, we develop an evolved service encounter framework and, in doing so, introduce the concept of counterfeit service, interspecific service (AI-to-human), interAI service (AI-to-AI), and offer a research agenda focused on the implementation of AI in dyadic service exchanges.

### 1. Introduction

The World Economic Forum cites artificial intelligence (AI) as the center of the world's current technological revolution. AI is attributed with transforming the way people “work, live and relate to one another” (Schwab, 2016), a transformation that will no doubt extend rapidly to frontline service encounters. While traditional exchanges between human customers and human frontline employees remain commonplace, AI is playing an increasing role. AI herein refers to both non-human customers (AI customer) and employees (AI FLE) substituting for a human counterpart in frontline encounters, and is defined as machines exhibiting facets of human intelligence (Huang & Rust, 2018). AI FLEs independently interact with customers on behalf of the firm. For example, customers checking into a hotel might receive a text from an AI asking if they are satisfied with their room. On the customer side, recent innovations have resulted in AI customers (e.g., digital assistants) capable of contacting a firm on their owner's behalf (Goode, 2018). In particular, a digital assistant can now book a salon

appointment or a make a restaurant reservation in a near-perfect human voice criticized for “fooling” its human exchange partner. In short, AI is radically reshaping service encounters as it transforms existing interactions and enables new interactions at the service frontline.

The notion individuals, customer or frontline employee, may not know they are interacting with an AI exchange partner during a routine frontline service encounter is due to recent AI advancements. While early chatbots were designed to speak clearly and concisely (i.e., robotically), chatbots 2.0 are programmed to be “perfectly imperfect” in their imitation of humans (Byrne, 2018). As a result, a reported 50% of customers who have interacted with AI are unaware their service exchange partner was non-human (Hyken, 2017b). Efforts to design AI agents difficult or impossible to delineate from humans, and potential lack of awareness regarding the presence of AI in dyadic service exchanges, lead to important ethical questions with far-reaching implications. Interestingly, AI playing the role of service employee has been referred to as “forged labor” (Kaplan, 2015). As such, humanlike AI not identified as non-human create a forged service exchange of

\* Corresponding author.

E-mail address: [sgrobinson@ua.edu](mailto:sgrobinson@ua.edu) (S. Robinson).

<https://doi.org/10.1016/j.jbusres.2019.08.038>

Received 8 February 2019; Received in revised form 25 August 2019; Accepted 26 August 2019

0148-2963/© 2019 Elsevier Inc. All rights reserved.

sorts. We advance humanlike AI creates a counterfeit service encounter if the customer or frontline employee (FLE) is unaware they are interacting with a non-human partner. As AI continues to become more humanlike, opportunities for counterfeit service encounters will only increase.

The increasing prevalence of AI in service encounters suggests it provides customers and firms with some net benefit. In support of this notion, several researchers have found such technologies can positively influence customer perceptions (Holzwarth, Janiszewski, & Neumann, 2006; Verhagen, Van Nes, Feldberg, & Van Dolen, 2014). However, research on the impact of an AI actor, in a traditionally human-to-human service encounter is in an early stage. Additionally and not surprisingly, given the recent emergence of humanlike AI, little research has investigated how AI, in an FLE or customer role, affects humans in the dyadic service encounter. Work in this area is needed given the increasingly humanlike characteristics of AI and use of chatbots, email, and text messages as a frequent channel for service encounters.

In this paper, we develop an organizing framework delineating between encounter types in which actors (customer or FLE) can either be human or AI (see Fig. 1). Further, we consider the issue of whether one actor is aware the other is AI. We discuss pertinent research questions, propose the concept of counterfeit service encounters, and outline how such encounters may impact the customer, FLE, and firm. We hope this evolved framework will support a research agenda focused on the distinct aspects of AI in dyadic service encounters. As such, this work is organized as follows: first, we define and differentiate between traditional human-to-human encounters, and encounters in which AI plays the role of human FLE or customer (AI-to-human), or both FLE and customer (AI-to-AI). Second, we present a literature review and research agenda for each type of service encounter identified, as well as highlight the potential for counterfeit service encounters. We also discuss associated implications for core service concepts and the overall service experience. Lastly, we conclude with a discussion of the framework's managerial relevance and overarching evolved service encounter issues.

## 2. Evolved service encounter framework

The term “service encounter” describes an exchange between a firm and customer (Bitner, 1990; Voorhees et al., 2017), yet this conceptualization does not currently provide sufficient insight into the evolving technological nature of the actors (i.e., human or AI) participating in the exchange. Service encounters have been labeled as social encounters (McCallum & Harrison, 1985), and defined as “human interactions” or dyadic exchanges between a human customer and human employee (Solomon, Surprenant, Czepiel, & Gutman, 1985 p. 101). As encounters evolve to include AI actors, and research extends beyond evaluating traditional human-to-human service encounters, to include AI-to-human, and AI-to-AI exchanges, an evolved framework, defining the type of encounter between FLE and customer is needed. Larivière et al.'s (2017) recent work on the evolution of service encounters highlights the need for research focused on technology substituting for service employees. As per the extant service encounter literature, and recent emphasis on the evolving nature of formerly human-to-human interactions (De Keyser, Köcher, Alkire, Verbeeck, & Kandampully, 2019; Larivière et al., 2017), the present framework focuses exclusively on dyadic encounters. FLEs and customers participating in an exchange may be human or AI substituting for a human, and accordingly the axes below represent the possible actors, and each quadrant is defined based upon its composition.

## 3. Review and research agenda

Given the rapid advancement and usage of AI within exchanges between customer and firm, and substantive differences compared to

less sophisticated technologies (e.g., AI has the ability to learn, process affect, mimic human characteristics), researchers and practitioners alike will benefit from guidelines on how to conceptualize encounters in which the exchange is characterized by an FLE-customer interaction which may include an AI actor. Our 2 (FLE: human vs. AI) x 2 (Customer: human vs. AI) framework yields four distinct types of encounters: (1) interhuman (customer-to-FLE), (2) interspecific<sup>1</sup> AI customer (AI customer-to-FLE), (3) interspecific AI FLE (customer-to-AI FLE), and (4) interAI (AI customer-to-AI FLE). In the following sections, we provide a discussion of each quadrant of the framework focused primarily on interspecific encounters, define counterfeit service encounters, and explicitly identify research questions that, if addressed, will advance knowledge on evolved dyadic service encounters (see Table 1).

### 3.1. Interhuman service encounters

The interhuman, or human-to-human, quadrant illustrates service encounters in which FLE and customer are both human. As expected, these encounters have historically received the most attention from researchers and practitioners. Undoubtedly, interhuman service encounters will continue to be extremely important given many service exchanges require a conventional customer-FLE interaction (Liao & Chuang, 2007). However, as AI technologies continue to evolve, and AI actors take on FLE and/or customer roles within dyadic exchanges, a number of research questions comparing interhuman service encounters to interspecific, or interAI encounters, emerge. In addition to comparisons between encounter types, demonstrating how interspecific encounters may impact subsequent interhuman encounters should be considered. In short, due to the growing prevalence of AI FLE and AI customer actors, the focus of this quadrant is on how interhuman encounters may compare to interspecific encounters.

#### 3.1.1. Research questions

As AI actors evolve to play an important role in a number of service encounters, exchanges characterized by high affect, perceptions of risk, personalization, long duration and/or intimate interaction, in which customers rely on verbal and non-verbal displays of FLEs' signs of attention and assurance (Gabbott & Hogg, 2001; Lloyd & Luk, 2011; Patterson, 2016; Raajpoot, 2004) may be difficult to replace with an AI actor playing the role of FLE or customer. One such example is a service (e.g., medical and legal services) in which customers are dependent on an FLE's knowledge and expertise, and unable to confidently evaluate aspects of the service (Patterson, 2016).

Similarly, for services in which the failure to convey empathy and care for customers reduces customer satisfaction (Webster & Sundaram, 2009), AI may be an unsuitable FLE replacement. Furthermore, for emotionally charged service encounters due to a service failure (Rafaeli et al., 2017) or nature of the service (e.g., medical testing, funeral services, wedding planning) (Delcourt, Gremler, De Zanet, & van Riel, 2017), a human FLE may reflect respect and appreciation for customers who might feel discomfort, insulted or offended (Dallimore, Sparks, & Butcher, 2007; Rafaeli et al., 2017), given that emotionally charged service encounters require FLEs to display authentic positive or negative emotions to satisfy customers' need for empathy and understanding. Here, consumers may perceive the affect conveyed by AI to be insincere and artificial. The usage of an AI actor may not be ideal in these situations, despite potential efficiency gains. Hence, future research might investigate whether fast and convenient service, provided by an AI FLE, attenuates customer need for affect, or personalized service. Also, there may be interhuman encounters in which the human

<sup>1</sup> The term interspecific is used to describe interactions between two distinct species (Hacker, 2009; Pantel et al., 2017; Schalow, 2015), such as human and AI.

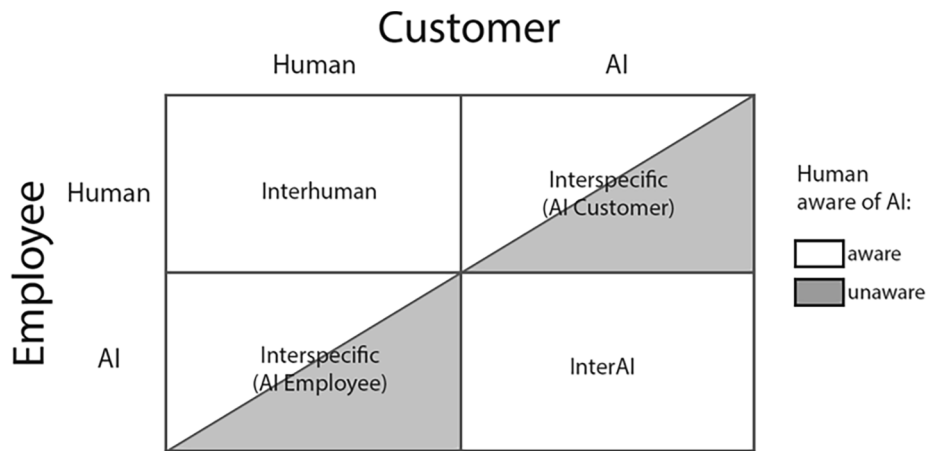


Fig. 1. Evolved service encounter framework.

**Table 1**  
Managerial issues by encounter type.

Managerial Issues by Encounter Type	Related Research Questions
<i>Interhuman</i> Selecting the best FLE (human or AI) for emotionally charged encounters Managing perceived risk and perceived control in the service encounter Understanding how customer value is generated Creating and sustaining strong social connection	Under what circumstances (e.g., high affect situation) do customers prefer working with AI FLEs over FLEs? Compared to FLEs, are AI FLEs able to fulfill a customer’s need for emotional exchange? Does expedited service via an AI FLE attenuate risk compared with a FLE? Does an AI FLE’s ability to deliver extensive information, on demand, provide cognitive control and allow the customer to better cope with emotions? When equally matched on meeting customer preferences, do customers value suggestions from human FLEs more than AI FLEs? Do customers prefer to interact with a known human FLE over an AI FLE if the latter has knowledge of purchase history and preferred style? How do FLEs feel about dealing with AI customers? Do exchanges with AI customers provide an FLE with an opportunity to recharge? What FLE personal characteristics (e.g., emotional intelligence) moderate the preference human vs. AI customer encounters? Are customers willing to accept AI as a substitute for FLEs, and under what conditions?
<i>Interspecific – AI Customer</i> Managing FLE emotions Rethinking FLE status and rank in the service encounter	Do FLEs treat AI customers differently than human customers? Do they experience psychological discomfort as a result? What FLE individual differences impact deferential treatment of an AI vs. human customer? How does the ability to customize an AI customer, impact the human FLE? How do AI customers impact FLE metrics (e.g., engagement, satisfaction, burnout)? Will high-wage work will be characterized by the satisfaction of working with other humans, while low-wage FLEs increasingly interact with AI?
<i>Interspecific – AI FLE</i> Managing customer communication and emotions	Do customers feel negative affect (e.g., guilt, shame, discomfort) during or after interspecific encounters with an AI FLE exchange partner as a result of the way they communicate with the technology? Does natural communication between AI FLE and customer improve the interaction and customer evaluations? Do AI FLEs generate customer discomfort and threaten customer human identity perceptions?
<i>InterAI</i> The role of customer control and trust Generating positive word of mouth Managing service failure attribution	Do customers benefiting from interAI encounters trust the firm more given the apparent loss of control? Is trust more important for service ultimately provided via interAI encounters? How will engagement behaviors, such as word of mouth (WOM), occur without a human customer actor? Who (customer or firm) is to blame when something goes wrong as a result of interAI encounters (e.g., wrong item received)?
<i>Counterfeit</i> Developing authentic and trustworthy service encounters	Is it unethical for an AI FLE or AI customer to not disclose its non-human nature? How do counterfeit encounters impact the customer’s experience? How do counterfeit encounters impact the FLE’s experience? What affect do counterfeit encounters have on subsequent encounters (both customer and FLE)? What are the societal impacts of such encounters? How are the costs (e.g., societal, economic) of counterfeit encounters assessed?

FLE lacks proper empathy or is offensive, and the customer prefers interacting with an AI FLE. More research is needed to understand when and how interspecific interactions may be preferable to inter-human encounters.

Some customers may care more about the social elements of service

encounters rather than the service itself, and AI may be an unsuitable actor (FLE or customer) replacement. Relationship-motivated customers expecting communal relationship with FLEs (Scott, Mende, & Bolton, 2013) welcome emotional expression (Lee & Ching Lim, 2010; Lim, Lee, & Foo, 2017), and look for non-verbal cues to reduce

ambiguity (Hennig-Thurau, Groth, Paul, & Gremler, 2006; Patterson, 2016; Söderlund & Rosengren, 2008), feel comfortable (Lloyd & Luk, 2011), build trust (Gabbott & Hogg, 2001; Sharma & Patterson, 1999), and develop rapport (Gutek, Groth, & Cherry, 2002; Medler-Liraz, 2016). Although AI technology can outperform humans in reliability and accuracy (e.g., task-related aspects) (Meuter, Bitner, Ostrom, & Brown, 2005), it may lack rich communication (Miyazaki, Lassar, & Taylor, 2007) and emotion (Grougiou & Pettigrew, 2011). The absence of these distinguishing characteristics of interhuman interactions may have adverse results on customer perceptions of trust and feelings of comfort during the service encounter (Gabbott & Hogg, 2001). Future research could explore if AI actors are able to recognize and respond to emotions in a way that may fulfill a customers' need for emotional exchanges. For professional services characterized by high information asymmetries for example (e.g., medical procedures), an AI-powered chatbot could be "on call" 24 h a day responding to customer queries at any point in time. Future research could examine if delivering extensive or highly accessible information through AI provides customers with higher cognitive control and promotes better coping skills.

Human FLEs may share many similarities with customers such as background, physical appearance, or hobbies (Crosby, Evans, & Cowles, 1990; Dion & Borraz, 2017; Pounders, Babin, & Close, 2015). In turn, customers may relate to them when engaging in purchase decisions (Argo, Dahl, & Manchanda, 2005; Dion & Borraz, 2017), seeking product advice, forming brand perceptions (Dion & Borraz, 2017), and developing commercial relationships (Gremler & Gwinner, 2000; Medler-Liraz, 2016; Scott et al., 2013). Interestingly, there are instances of customers relying on service employees as anchors of how they will appear or feel when they use a product or service. For example, Eli, Bar-Tat, and Kostovetzki (2001) showed the appearance of a dentist's teeth is important in forming customer perceptions of his/her professionalism and social skills. Dion and Borraz (2017) demonstrated FLEs and customers of luxurious stores look similar not only in their dress but also in their body language, emotions, and speech. These findings suggest interhuman encounters will be more effective for services in which customers relate to employees who consume similar services as customers, compared with encounters in which AI is acting as an FLE.

Consumption can be a self-defining and self-expressive behavior. People often choose products and brands that are self-relevant and communicate a given identity: "consumption serves to produce a desired self through the images and styles conveyed through one's possessions" (Thompson & Hirschman, 1995, p. 151). As such, consumers make their identities tangible, or self-present, by associating themselves with material objects and places. Relatedly, in an effort to obtain one's desired selves, consumers engage in consumption activities to enhance their self-definition and self-presentation (Schau & Gilly, 2003). Important information related to a customer's identity may be revealed when they are engaged in search behaviors (e.g., webrooming). It is not unrealistic to believe AI might be programmed to monitor behaviors and patterns, to ultimately identify a customer's desired self. Future research could also examine consumer response to AI FLEs, powered by deep learning, that provide suggestions matching their preferences and desired self. For example, customers may prefer a transactional relationship with a human FLE, over an interaction with an AI FLE that knows detailed information about them, such as the content of 'their wardrobe, purchase history, or preferred style.

It is well established FLEs also benefit from interactions with customers. Engaging in emotional labor for long periods is challenging and can cause the FLE to potentially suffer from emotional exhaustion, cognitive overload, and job burnout (Chen & Kao, 2012; Dallimore et al., 2007; Rafaeli et al., 2017), resulting in negative consequences to the FLE and firm (Grandey, Dickter, & Sin, 2004; Rafaeli et al., 2017; Söderlund, 2017). Interestingly, social connections with others can circumvent FLE overload and exhaustion (Maslach, Leiter, & Jackson, 2012). Relatedly, research shows intimate customer-to-employee relationships are more resistant to drops in service performance (Lim

et al., 2017; Sharma & Patterson, 1999). Replacing the customer with AI, in these exchanges, may have a detrimental impact on FLEs. Future research should explore boundary conditions for this effect.

Moreover, FLE-customer relationship bonds are often critical to a firm's sales (Verhoef, 2003) and important to the customer. In such relationships, it may even be difficult to replace an FLE with another human FLE (Beatty, Mayer, Coleman, Reynolds, & Lee, 1996; Gutek et al., 2002) because of a shared history of interactions (Beetles & Harris, 2010). As such, any attempt to replace the FLE with AI may negatively impact the firm and certainly offers an interesting area of research with strong theoretical and managerial implications.

### 3.2. Interspecific service encounters: AI customer

The majority of AI is firm or government owned, and therefore likely to be a substitute for an FLE versus customer (Anderson, Rainie, & Luchsinger, 2018). However, customers may also be replaced by AI in routine service encounters, as current advances in technology make it possible for customers to utilize AI assistants to engage in exchanges with FLEs. Borrowing a term from ecology, interactions between two species such as humans and AI, can be characterized as interspecific (Hacker, 2009; Pantel et al., 2017; Schalow, 2015). This initial interspecific section will focus on potential outcomes of AI customer-to-FLE exchanges.

To date, the vast majority of research dealing with the presence of AI in service encounters is concentrated on the impact of AI replacing or augmenting an FLE. Early predictions (Simon, 1965) stated smart machines would be capable of replacing the human workforce, regardless of the type of work. In recent years, AI quantitative, computational, and analytical capabilities surpassed humans in complex tasks (Jarrahi, 2018). Currently, AI frequently replaces FLEs at the task level, but eventually, AI FLEs will be capable of performing intuitive and empathetic tasks (Huang & Rust, 2018).

However, situations in which FLEs are human and customers are AI poses an interesting set of research issues not yet investigated. Only the business press has commented on this type of encounter and has done so with contradictory opinions. For example, a highly publicized AI assistant, designed to act on behalf of customers (i.e., Google Duplex) raised enthusiasm, because the disembodied AI sounded amazingly human. It was able to navigate the minor difficulties typical of human-to-human communication and even uttered the occasional "mmhm" to make sure the human exchange partner knew the AI was still present (Pressman, 2018). What's more, the AI generated concern that should it fall into the wrong hands, the outcome could be a deluge of "sneaky robot spam calls" (Wong, 2018, p. 21), and its use would ultimately result in a reduction of actual human interactions (Madrigal, 2018) that satisfy both customers and FLEs social needs. Interspecific encounters with AI customers may affect the way FLEs perceive and enact their service role compared to traditional interhuman encounters, and it is likely that the impacts of interspecific encounters could be both positive, and negative.

#### 3.2.1. Research questions

Much of the work performed by FLEs is not defined as physical labor, but rather as emotional labor. Emotional labor is the process of regulating one's feeling and also the expression of those feelings to achieve organizational goals (Grandey, 2000). There are two generally recognized types of emotional labor: deep acting and surface acting. Surface acting occurs when, as per management instructions, FLEs must "fake" an attitude or emotion such as happiness. Often this is done to align employee behavior with brand image, resulting in positive outcomes for the firm (Sirianni, Bitner, Brown, & Mandel, 2013). However, there is a downside for the FLE. Prior research has shown surface acting decreases employee engagement and increases employee turnover. Conversely, when deep acting, the employee attempts to empathize with customers, by actually relating to the emotions the customer is

experiencing. Although deep acting is less associated with adverse outcomes for the employee, it still requires emotional resources (Brotheridge & Grandey, 2002). However, social norms do not prescribe humans engage in emotional labor when interacting with machines (Taylor, 2018). Social norms evolved to inform interactions between humans, including interhuman frontline service encounters. As such, it seems possible FLEs may not feel particularly obligated to engage in emotional labor when the customer is non-human. For example, it seems unlikely FLEs taking reservations for a salon or restaurant would bother to engage in surface or deep acting when setting up an appointment with an AI customer. Therefore, interactions with an AI digital assistant, acting on behalf of the customer, may provide FLEs with an opportunity to take a break from engaging in emotional labor. More research is needed to understand to what extent this reasoning holds.

Conversely, taking a break from emotional labor may not be as easy as it seems. After all, AI digital assistants often exhibit human mannerisms. Research has repeatedly observed individuals “mindlessly” apply social rules to computers and other artificial entities, especially when these entities display human characteristics or engage the user in social interactions (Hertz & Wiese, 2018; Moon, 2003; Nass & Moon, 2000). FLEs who find it difficult to “switch modes” when they encounter an AI customer may experience psychological discomfort given that they are interacting with a humanlike customer they know to be a machine. Relatedly, treating a humanlike AI as less-than-human may induce feelings of discomfort or dissonance (Lee & Ching Lim, 2010). Future research could examine the prevalence of this effect, and the extent to which it might be moderated by FLE individual differences such as social intelligence, or need for belongingness (Leary, Kelly, Cottrell, & Schreindorfer, 2013; Lee & Ching Lim, 2010).

Firms will likely have some control over how their FLEs interact with AI customers. Current examples (e.g., Google Duplex) provide firms with the ability to accept or decline calls from the AI customer. In other words, firms have interfaces that can control how, or whether, these digital assistants interact with employees. Relatedly, allowing FLEs to control how AI customers address them may positively impact interspecific encounters when an AI customer is present. It is not a stretch to believe the technology will be able to recognize which employee answers the phone. Even if employees do not offer their name when answering the phone (e.g., “Thanks for calling \_ vs. thanks for calling \_\_, this is Jeff”), AI can be trained to recognize people by voice (Townsend, 2017), and adapt its voice, tone, conversational patterns based upon the FLEs preferences. Relevant to a futuristic scenario where AI assistants take a physical form, there are already consumer-grade robots who are capable of recognizing 1000 different people based on facial features alone (Palmer, 2019). There may be a positive impact associated with allowing an FLE to customize how AI customers speak to them. Research suggests perceived control is associated with a number of positive social outcomes (Spector, 1986). Similarly, successful co-production can increase the utility derived from the co-produced service (Bendapudi & Leone, 2003).

Additionally, interspecific encounters may be interpreted, by the FLE, as a commentary on the employee's status. Social norms would prohibit sending an “assistant” to interact with those of equal social status. As such, when a customer employs AI to engage with the FLE, it may be perceived as a slight. This effect, however, might be moderated by the extent to which the FLE uses their own AI digital assistant. If the FLE uses AI in similar interactions, it is less likely they would interpret customer use of an AI digital assistant negatively. However, one must also consider “fundamental attribution error” (Jones & Harris, 1967) whereby individuals attribute their own bad behavior to external forces (e.g., I am too busy) and other people's bad behavior to internal factors (e.g., they are a jerk). Future research is needed to better understand how customer use of AI will impact important FLE metrics (e.g., engagement, satisfaction, burnout).

Presumably, many FLEs pursue jobs in the service industry because they enjoy working with people. For example, they might self-identify

as a “people person” or derive utility from interacting with other human beings. AI customers have the potential to reduce, or even eliminate, these interactions. A FLE who deals exclusively with digital assistants is effectively little more than a data entry professional, taking data from one system and entering it into another. In other words, AI digital assistants may transform the FLE's job into something a “people person” would not pursue. The opportunity to connect with other humans is also cited as a factor driving job satisfaction among service employees. Also inherently absent from interspecific encounters are the social benefits that accrue from interhuman encounters. For example, gratitude is identified in the literature (Palmatier, Jarvis, Bechhoff, & Kardes, 2009) as an outcome FLEs find particularly valuable. A thank you or compliment from an AI customer most likely has little meaning. An investigation on the likelihood high-wage work will be characterized by the satisfaction of working with other humans, while low-wage FLEs increasingly interact with AI could be impactful.

What's more, this change in job description and removal of traditional benefits (e.g., gratitude, rapport) has the potential to result in a self-identity threat for FLEs - especially those who self-identify as providers of high-quality customer service (Kraak, Lunardo, Herrbach, & Durrieu, 2017). Conversely, the increasing prevalence of AI customers may be welcomed by FLEs who do not find value in serving customers. In other words, the emergence of AI customers may be bad for a service organization's best employees and good for its worst employees. Perhaps there is even the potential for a vicious circle whereby AI customers result in decreased service quality, which prompts more customers to employ AI on their behalf, and so on. Such an effect would have significant strategic implications for organizations traditionally positioned as providers of exceptional customer service. Research is needed to determine if such an effect might occur and what managerial tactics (e.g., types of employee training) could be used to combat it.

### 3.3. Interspecific service encounters: AI FLE

While the interspecific encounter with an AI customer and human employee described above is a relatively new phenomenon, interspecific encounters in which the customer is human and the FLE is AI are not futuristic possibilities, but currently occurring with regularity across industries. Interspecific encounters with AI FLEs will likely continue to grow given related increases in firm revenue. MIT Technology Review reports 90% of firms using AI do so to improve the customer experience and increase revenue, and up to a staggering 50% of all customer inquiries are resolved through automated channels (Ciuffo, 2019). Automated chatbots interacting with customers are examples of interspecific encounters with an AI FLE, as are virtual assistants launched by retailers, which are capable of anticipating and placing orders, and reporting the status of deliveries. In 2017 alone, a financial services AI FLE in China handled 1.9 billion customer interactions covering more than 80 different banking services (DigFin, 2018). The hospitality industry is also utilizing AI FLEs. For example, one popular “virtual concierge” has been cited with engaging hotel guests via their mobile devices (e.g., texts upon check-in and throughout stay), leading to improved customer satisfaction scores, and 30% fewer service calls to hotel front desks (Singh, 2017; The Economist, 2018). Interspecific encounters between an AI FLE and human customer may affect the way customers perceive the firm, and enact their role compared to traditional interhuman encounters.

#### 3.3.1. Research questions

Customers interacting with AI FLE through voice, chat or text are known to adapt their behavior accordingly. Research by Hill, Ford, and Farreras (2015) demonstrates people change their communication styles when they are aware of speaking with an AI FLE instead of a human. More specifically, people interacting with AI FLEs use more, but shorter, sentences with a restricted vocabulary compared to people interacting with a human FLE. Additionally, research indicates

customers may interact rudely and make use of profanity with AI FLEs (Hill et al., 2015). This raises the question of whether or not customers might feel negative affect (e.g., guilt, shame, discomfort) during or after interspecific encounters with an AI FLE exchange partner, and if impolite behavior continues to occur during contiguous interhuman encounters, thereby negatively impacting the human FLE actor in future dyadic exchanges.

Mende, Scott, van Doorn, Shanks, and Grewal (2017) suggest interacting with AI may give rise to feelings of discomfort. Specifically, customers interacting with intelligent agents able to converse in near human terms may perceive a mismatch between the initially anticipated human behavior of the AI and the actual imperfect behavior displayed— a phenomenon typically referred to as the uncanny valley effect (Mori, 2012). Research is needed to understand how firms may attenuate this effect, and set proper customer expectations on AI FLE performance.

Further, customer attitudes towards technology and the extent to which they perceive AI as a threat to humanity may have a significant impact on their levels of discomfort when interacting with AI FLEs. Zlotowski, Yogeewaran, and Bartneck (2017) show autonomous robots evoke strong negative feelings as people experience both a realistic (i.e., robots as a threat to human safety, well-being, and resources) and identity (i.e., robots harming human uniqueness and distinctiveness) threat. Such feelings are theorized to originate from an in-group vs. out-group distinction, where AI is considered part of an out-group threatening the human in-group. Following similar reasoning leads to the question of how a perceived threat to human identity affects attitudes towards the firm, or general satisfaction in spite of the level of service provided by the AI.

### 3.4. Counterfeit service encounters

Both interspecific encounter quadrants, with AI customer or AI FLE, categorize two distinct service encounter scenarios. Such encounters currently include AI substituting for the customer in the form of a digital assistant, or firms employing AI FLEs to engage in tasks such as initiating or answering customer service calls, or texting or emailing customers to gauge satisfaction. Increasingly, companies employing customer-facing AI technologies attempt to deliver a customer experience “in which customers cannot tell if they are communicating with a human or a computer” (Hyken, 2017a). Their efforts are apparently successful, as a notable half of customers interacting with AI FLEs are unaware their exchange partner was non-human (Hyken, 2017b). Given advancements in AI technologies, which make it difficult or impossible to confidently distinguish between a human vs. non-human actor within an interspecific encounter, we further delineate between interspecific encounters in which the human exchange partner is aware vs. unaware of the non-human nature of the AI customer or AI FLE and label the latter as counterfeit.

Counterfeits have been described as having characteristics that are copied and indistinguishable from the original (Orth, Hoffmann, & Nickel, 2019), and defined as fictitious, imitation or insincere (Kuokkanen, 2017). As such, studies on counterfeiting often focus on the impact of deception (Eisend & Schuchert-Güler, 2006; Randhawa, Calantone, & Voorhees, 2015). Given attempts to make disembodied AI sound human via audible voice characteristics (e.g., mhmm) or programming AI to write “perfectly imperfect” text (Byrne, 2018), we assert interspecific encounters in which the AI actor (i.e., customer or FLE) is humanlike and indistinguishable from a human, and in which the exchange partner is unaware the AI actor is not human are deceptive, and by definition “counterfeit service encounters.”

At the product launch for one global brand’s AI assistant designed to substitute as a customer in routine service encounters with firms, the firm’s CEO stated the technology is able to understand the “subtle nuances” of human language and “brings together all our investments over the years in natural language understanding, deep learning, text to

speech” (Pichai, 2018). The AI assistant presented was indistinguishable from a human, and did not disclose itself as non-human to its service encounter exchange partner. This element of deception and lack of awareness by the human exchange partner raises concerns about the impact of interspecific encounters in which the AI actor is not disclosed as non-human, yet indistinguishable from a human (Lomas, 2018; NPR, 2018). A central concern is this type of encounter can create ancillary mistrust in subsequent unrelated interactions (Madrigal, 2018). Expectedly, the inability to detect a human voice or form from that generated by AI is cited as increasing the risk for deception (Meed, 2018), and is not viewed as innocuous (Marr, 2019). While not yet regulated, there is a growing consensus AI fabrication, defined as what a consumer sees or hears generated by AI, is not deceptive as long as the consumer is aware of its AI nature (Marr, 2019). Similarly, with regard to tangible products, the United Nations Office on Drug and Crime states “product counterfeiting is a form of consumer fraud: (if) a product is sold, purporting to be something that it is not” (UNODC, 2019 p. 174). The estimated \$1.82 trillion counterfeit product global market (Businesswire, 2018) has numerous federal and state laws which prohibit counterfeiting, and the negative impacts associated with product counterfeiting are considered to be “long-term, subtle and diffuse” (UNODC, 2019 p. 174). At present, undisclosed AI actors substituting as human are not formally regulated, nor tied to financial or non-monetary loss. Yet, concerns about trust erosion and its impact on a firm’s employees, customer, and society are fundamental when considering the impact of counterfeit service encounters. The European Commission recently classified “trustworthy AI” as an aspirational goal (Renda, 2019), and the IEEE technical professional association created guidelines calling for transparency (Lomas, 2018). UK’s British Standards Institute labeled deception, intentional or unintentional, as a societal risk and cautions such deception will negatively impact trust in the technology (PBSI, 2019). In the United States, the state of California recently passed a law requiring AI on social media platforms to identify itself as such (Simonite, 2018).

Disclosing the presence of an AI actor in the dyad, may soon be regulated or called-for standard practice given apparent societal and ethical concerns. However, general research on the impact of undisclosed AI on unaware human exchange partners, and subsequent firm, and societal outcomes is needed to assist consumers, firms, and policy makers as they consider the impact of AI actors in the role of customer or FLE in service encounters. Although fear over potential counterfeit encounters with AI are just beginning to emerge, similar concerns over deception in marketing and associated consumer reactions (Darke & Ritchie, 2007; Tessitore & Geuens, 2013, 2019), may provide researchers and practitioners with a relevant comparison.

### 3.5. InterAI service encounters

The average customer speaks with customer service employees 65 times per year. Annually, that adds up to more than 270 billion service calls, which cost the firm, on average about \$1 (USD) per call (Hashimi, 2017). Large expenses associated with handling customer service calls, coupled with attempts to improve the customer experience led businesses to employ advanced technologies designed to merge the contact center with AI-powered agents. These technologies are anticipated to be the future of customer care centers (iSymplify, 2018), which leads to an interesting potential encounter scenario given these same AI agents were also designed to serve as personal assistants for consumers. Service encounters of the near present, falling within the AI-to-AI encounter quadrant, will likely have a strong impact on the relationship between the customer and the firm. These encounters, aptly labeled as “interAI,” are defined as the intersection at which AI agents communicate with each other on behalf of both firm and customer.

Within interAI encounters, machines communicate with other machines remotely. These communications are largely inaccessible to humans, for example, this type of machine-to-machine communication

**Table 2**  
Core service topics - important research questions.

- How is *satisfaction* defined when the customer is AI?
- How is *customer loyalty* defined and developed in interspecific or interAI service encounters?
- Do the concepts of *inseparability* and *heterogeneity* of a service apply to interspecific and interAI service encounters?
- Will the value of *WOM* change as a result of interspecific or interAI encounters?
- What are the unique aspects related to *zone of tolerance* within interspecific encounters?
- Does the *service profit chain* model need to be reorganized to incorporate interspecific and interAI encounters?
- To what extent do interspecific and interAI encounters impact the *customer service journey*?
- Will AI FLEs outperform FLEs in terms of understanding/managing the *customer service journey*?
- Do interspecific encounters (negatively/positively) affect a firm's FLEs *engagement*?
- Are *service failures* equal across the evolved service encounter framework?

occurs every time a mobile phone synchronizes with a computer. Thus, imagining an AI customer will communicate with an AI FLE is not an unrealistic scenario. In fact, machine-to-machine communication occurs in smart services systems, defined as systems capable of self-detection and self-diagnostic functioning (Maglio, 2014), and is substituting for patient and practitioner in medical service exchanges in the form of wearable monitoring devices.

Smart services utilize AI to gather and analyze real-time data, and initiate purchases or other transactions (Allmendinger & Lombreglia, 2005). For example, consumer appliances (e.g., refrigerators) incorporated with sensors, control devices and connectivity can anticipate consumer needs, determine product expiration dates, and place orders with a retailer's AI. Similarly, a sensed home may collect and report data to a utility company. The firm's AI may then develop suggestions to reduce utility costs and provide the AI customer with information. Service exchanges within a medical context have also been altered by AI reporting medical information about a patient through wearables (e.g., diabetic monitoring) to a practitioner's AI which collects and analyzes patient data. In short, smart services and wearable technologies are examples of interAI encounters in which customer and firm communicate without human involvement. In addition to re-vamping longstanding conceptualizations of what constitutes a service exchange, these types of AI are likely to “play a significant role in extracting actionable insights” (Bresnick, 2018).

### 3.5.1. Research questions

While lauded for their efficiency, interAI service encounters need further investigation. There are several pressing questions for future research, such as how consumers will react towards exclusion from the service encounter. If a customer is substituted with an AI customer and the firm responds with an AI FLE, the customer is giving up control over the process perhaps in favor of convenience. This tradeoff suggests trust towards the service brand/provider would play an even more important role than it does in interhuman or interspecific service encounters. It also leads to questions related to how customer satisfaction is assessed, and how expectations are formed and confirmed given both are part of an iterative process.

AI may also act as a customer substitute during the pre-purchase and post purchase stage of the service experience; AI customers might anticipate customer needs, engage in the search for the best alternative and develop customer decision making criteria. This form of AI customer decision making leads to questions concerning the degree to which loyalty to a service provider will matter, or if customers will buy from a number of service providers based on interAI negotiations, or an AI customer's decision optimization. InterAI service encounters beg the question if and how engagement behaviors, such as word of mouth (WOM), occur without a human customer actor. Perhaps WOM might

be utilized by AI, or spread by AI leading to questions on WOM valence. This also leads to an interesting question about increases in the accuracy of evaluations and, in turn, perhaps more or less meaningful data.

Additionally, AI encounters will likely face questions regarding how customers will react towards misunderstandings and service failures. When service failures happen, customers tend immediately to look for causes (Van Vaerenbergh, Orsingher, Vermeir, & Larivière, 2014). In interAI service encounters, this search could be impossible or extremely difficult, resulting in negative affective reactions and profound customer dissatisfaction. Although AI solutions can create great value, it is important to understand firms will face challenges, specifically when it comes to loyalty and brand experience. A primary question to be addressed centers on whether it is the AI customer or AI FLE actually providing the service.

## 4. Evolved service encounters research agenda

This conceptual article presents an evolved service encounter framework, which is based on AI substituting for the role of customer or FLE and premise traditional interhuman service encounters may have little in common with interspecific, and interAI service encounters in terms of impact on customer, FLE, and firm. What's more, we recognize the importance of investigating the impact of AI in the service environment, and acknowledge rarely does a single service encounter constitute a service experience (Lemon & Verhoef, 2016). As such the following section is organized around the notion core service concepts may be impacted by AI's role in service encounters, and concludes with a summation of related research questions (see Table 2).

### 4.1. Evolved service encounters are evolved service experiences

Ostrom, Parasuraman, Bowen, Patrício, and Voss (2015) assert, “the importance of service research and the need for new service-related knowledge have never been greater” (p. 127). This increasing importance is due to the rapid pace of fundamental change occurring within the context of services – to both service delivery and experience (Ostrom et al., 2015). Advances in technology, are impacting customer and firm, and creating opportunities for new avenues of research such as smart services, the Internet of Things, cloud computing, mobile technology, social network technology and big data (Rust & Huang, 2014). While it is undeniable quickly changing technology is creating opportunities to study new service topics, we maintain the evolved service encounter framework proposed here creates an opportunity to re-evaluate a number of core service topics that will undoubtedly be impacted by AI customers and/or AI FLEs substituting for humans within a given exchange.

With regard to satisfaction (see Oliver, 1980), for instance, the expectancy disconfirmation paradigm is likely to remain the right framework to understand how humans evaluate the service. However, for an AI actor, satisfaction assessments are likely to differ compared to its human counterpart, and be the result of it being able to deliver a specific outcome for which it is programmed. As a result, it is likely solely dependent on a cognitive evaluation, involving no emotion, and driven by a multitude of calculated metrics (e.g., successful outcome: yes/no, timeframe parameters, etc.). Moreover, this type of satisfaction is likely to be more stable as the zone of tolerance should be less dependent on context. Loyalty, as well, will likely be formed differently within interspecific and interAI encounters compared to interhuman exchanges. For instance, AI customers may employ rational criteria human customers are unlikely to objectively maintain, raising the question if brand loyalty will still exist in the future. As AI actors use rational criteria to make choices (e.g., price, timing), being included in the consideration set and finally being chosen may require marketers to rethink their strategies. This might include determining and matching the criteria AI customers use for selection – a practice that may resemble today's search engine optimization – or establishing partnerships with firms



developing the algorithms behind AI customers (Dawar, 2018). As such, loyalty may become more about criteria optimization rather than emotional connections, which currently characterizes services.

Relatedly, the overall service journey is likely to undergo important changes as interhuman, interspecific, and interAI encounters alternate across the various journey stages.

While recent research addresses the impact of AI FLEs replacing human FLEs, and the future of the workplace (Frey & Osborne, 2017; Huang & Rust, 2018), little is known about the implications of human FLEs co-working with an FLE AI (De Keyser et al., 2019). Interspecific encounters with an AI FLE are dyadic, however, the impact of such encounters must be considered beyond their initial impact on the customer, and include the impact on human FLEs who may be working alongside the AI FLE. This is important given service encounters are contiguous (Allen, Brady, Robinson, & Voorhees, 2015) and an interhuman encounter may follow an interspecific encounter. The impact of an AI FLE on its human counterpart has important implications for subsequent interhuman encounters. For example, imagine a guest checks into a hotel and AI FLE texts the customer to ask about her experience, the customer may respond with a routine inquiry about restaurant hours or reservations, which is quickly answered by the AI FLE. While the reassignment of these tasks to the AI FLE allow the human FLE to address more complicated service issues, the AI FLE might receive the praise, as frequently evidenced by hotel reviews on a popular travel website (e.g., “My stay at the [hotel] was awesome, and I had the best concierge you could ask for!! Her name is [AI FLE].”). In these situations, the AI FLE receives the credit for the prompt and attentive service, while human FLEs working in the background fails to be acknowledged. Employee recognition, however, is widely considered one of the key drivers of employee engagement (Brun & Dugas, 2008). For instance, Brun, Biron, Martel, and Hivers (2003), show lack of recognition constitutes a major risk factor for psychological distress in the workplace. The recognition received by customers is pivotal to employee engagement (Brun & Dugas, 2008; Verleye, Gemmel, & Rangarajan, 2016). When customers are unaware of the role employees play, recognition might be significantly lowered. This, in turn, may negatively impact employee engagement. The above suggests a lack of role transparency may be a major issue for human FLEs. A global survey of 3000 employees across eight countries (Workplace Institute, 2018) found employees' biggest concern is not AI infiltrating the workplace, but rather the lack of transparency in its implementation and usage. An implication for FLEs is they may complement the work of an AI FLE without disclosing the AI FLE presence to customers. This nondisclosure could create possible role conflict, which may have a negative impact on human FLE employee such as increased job dissatisfaction, role stress, turnover, burnout, and on firm outcomes in the way of fewer organizational citizenship behaviors (Chung & Schneider, 2002).

On a positive note, the introduction of AI FLEs may also lead to a more interesting and challenging work environment for human FLEs (Wirtz et al., 2018). As stated above, AI FLEs often handle routine interactions with customers, allowing human FLEs to focus on more complex customer interactions. One such example is conversational software processing large numbers of incoming customer queries. More precisely, the software analyzes incoming messages and automates iterative requests. With the help of such AI FLEs, human FLEs no longer deal with trivial customer requests but instead invest their time dealing with higher-level tasks. Firms utilizing such technology may significantly improve employee retention metrics, in addition to customer call handling times (Vanderbroeck, 2018). Hence, improvement to the work environment, due to AI FLEs, may lead human FLEs to consider AI as valued co-workers/partners and increase levels of employee engagement (Crawford, LePine, & Rich, 2010). As such, research to determine the impact of AI FLEs on subsequent interhuman encounters via how they affect their human FLE counterparts is warranted.

Interestingly, AI may improve a customer's experience by quickly assessing the complexity of a situation and responding at an expedited

rate compared to human FLE who “cannot be expected to understand a customer's entire history and derive their own insights from it in real time” (Theil, 2019). The role of human actors may be restricted to specific parts of the service journey such as actual consumption, with AI actors dominating the early stages of the journey (Dawar, 2018). In addition, as AI's abilities continue to evolve; automated and virtually human-free journeys may become standard for some services.

Many other service concepts are set to undergo a similar evolution and will require new research to assess whether fundamental knowledge as it is today still applies. Some additional topics we think are relevant include engagement (e.g., AI actors ability to promote a firm via word-of-mouth, or provide feedback), service failure/recovery (e.g., the ability for AI actors to complain or successfully provide service failure resolution), employee/customer empowerment (e.g., AI actor freedom), service profit chain (e.g., AI's impact across the model), and defining service characteristics (e.g., AI may impact concepts of heterogeneity and inseparability). It seems clear many fundamental premises need to be questioned and re-investigated. We urge future research to further consider the impact of AI on service core concepts as it dominates change within the service space, so that the discipline can co-evolve.

## 5. Overarching evolved service encounter issues

A recent Accenture report states by the year 2035 AI has the potential to boost profitability by 38% on average and create an economic boost of \$14 trillion across 16 industries in 12 economies (Purdy & Daugherty, 2017). AI's profit boosting promise and technological advances are driving change at a rapid pace. As such, the organizational frontline is facing unprecedented evolution, as AI technologies become a routine element of the service environment. This work introduces an evolved framework delineating the various encounter types resulting from introducing AI at the service frontline. Specifically, we distinguish four service encounter types: interhuman (FLE-to-customer), interspecific AI customer (AI customer-to-FLE), interspecific AI FLE (customer-to-AI FLE), and interAI (AI FLE-to-AI customer). We conceptually develop each encounter type, and provide specific implications, with supporting research questions. Also, we introduce the concept of counterfeit service encounters, as human FLE or customer may not recognize an AI actor as non-human, raising questions on the potential for trust erosion and need for AI transparency

Frameworks, such as the present, provide a way to organize and summarize past research in order to “provide a clear, simplified perspective to illuminate what is known and not known” (Jaworski, 2011, p. 217). One of the limitations of proposing a framework focused on what is “not known,” is a lack of immediately actionable insight and the illusion of a lack of managerial relevance. However, managerial relevance is both broad and nuanced with multiple categorizations, for example “one class of relevance is for immediate action” and another class “has the potential to affect deeper thinking in the future”; Jaworski, 2011 the latter is viewed equally as important as the former given “certain pieces of marketing knowledge may trigger deep thought but no immediate action” (Jaworski, 2011, p. 214). When research begins to address unanswered questions, the compilation of evidence or comprehensive knowledge becomes actionable and managerially relevant (Jaworski, 2011). We propose existing knowledge on the use of AI as a substitute for customer or FLE is inadequate and many questions need attention in order to generate sound, big-picture focused implications.

Managers will undoubtedly be tasked with answering overarching service encounter questions such as “in which circumstances should firms invest in AI?,” “which encounter type will have the greatest impact on the firm?,” “what is the optimal combination of human/AI FLE investments?,” “how can hiring be optimized based upon encounter type?,” or “which evolved service encounter type optimizes a firm's goals (e.g., customer experience, efficiency, strategic advantage)?” –

one of the advantages of developing an evolved service encounter framework, and associated research questions focused on each encounter type, is the foundation it provides to further develop and answer these all-important, overarching service encounter questions. Overall, it is our hope this paper fosters empirical research on AI in service encounters as scholars and practitioners work to understand the corresponding opportunities, challenges, and most importantly, impact on business and people.

## References

- Allen, A. M., Brady, M. K., Robinson, S. G., & Voorhees, C. M. (2015). One firm's loss is another's gain: Capitalizing on other firms' service failures. *Journal of the Academy of Marketing Science*, 43(5), 648–662.
- Allmendinger, G., & Lombreglia, R. (2005). Four strategies for the age of smart services. Retrieved from <https://hbr.org/2005/10/four-strategies-for-the-age-of-smart-services>.
- Anderson, J., Rainie, L., & Luchsinger, A. (2018). Artificial intelligence and the future of humans. Retrieved from <https://www.pewinternet.org/2018/12/10/artificial-intelligence-and-the-future-of-humans/>.
- Argo, J. J., Dahl, D. W., & Manchanda, R. V. (2005). The influence of a mere social presence in a retail context. *Journal of Consumer Research*, 32(2), 207–212.
- Beatty, S. E., Mayer, M., Coleman, J. E., Reynolds, K. E., & Lee, J. (1996). Customer-sales associate retail relationships. *Journal of Retailing*, 72(3), 223–247.
- Beetles, A. C., & Harris, L. C. (2010). The role of intimacy in service relationships: An exploration. *Journal of Services Marketing*, 24(5), 347–358.
- Bendapudi, N., & Leone, R. P. (2003). Psychological implications of customer participation in co-production. *Journal of Marketing*, 67(1), 14–28.
- Bitner, M. J. (1990). Evaluating service encounters: The effects of physical surroundings and employee responses. *The Journal of Marketing*, 69–82.
- Bresnick, J. (2018). Top 12 ways artificial intelligence will impact healthcare. April 30 <https://healthitanalytics.com/news/top-12-ways-artificial-intelligence-will-impact-healthcare>.
- Brotheridge, C. M., & Grandey, A. A. (2002). Emotional labor and burnout: Comparing two perspectives of “people work”. *Journal of Vocational Behavior*, 60(1), 17–39.
- Brun, J.-P., Biron, C., Martel, J., & Hivers, H. (2003). *Evaluation of mental health: An analysis practices of human resources management*. Montreal: Institute for Research Robert-Sauve in health and in security work.
- Brun, J. P., & Dugas, N. (2008). An analysis of employee recognition: Perspectives on human resources practices. *The International Journal of Human Resource Management*, 19(4), 716–730.
- Businesswire (2018, May 15). Global brand counterfeiting report. Retrieved from <https://www.businesswire.com/news/home/20180515005775/en/Global-Brand-Counterfeiting-Report-2018-2020—ResearchAndMarkets.com>.
- Byrne, K. (2018, June 20). Chatbots: Your new best friend? Retrieved from <https://www.independent.ie/life/chatbots-your-new-best-friend-37023285.html>.
- Chen, C. F., & Kao, Y. L. (2012). Investigating the antecedents and consequences of burnout and isolation among flight attendants. *Tourism Management*, 33(4), 868–874.
- Chung, B. G., & Schneider, B. (2002). Serving multiple masters: Role conflict experienced by service employees. *Journal of Services Marketing*, 16(1), 70–87.
- Ciuffo, J. (2019, January 31). How global companies are winning at AI deployment. Retrieved from <https://www.genesys.com/blog/post/mit-technology-review-insights-how-global-companies-are-winning-at-ai-deployment>.
- Crawford, E. R., LePine, J. A., & Rich, B. L. (2010). Linking job demands and resources to employee engagement and burnout: A theoretical extension and meta-analytic test. *Journal of Applied Psychology*, 95(5), 834.
- Crosby, L. A., Evans, K. R., & Cowles, D. (1990). Relationship quality in services selling: An interpersonal influence perspective. *The Journal of Marketing*, 68–81.
- Dallimore, K. S., Sparks, B. A., & Butcher, K. (2007). The influence of angry customer outbursts on service providers' facial displays and affective states. *Journal of Service Research*, 10(1), 78–92.
- Darke, P. R., & Ritchie, R. J. (2007). The defensive consumer: Advertising deception, defensive processing, and distrust. *Journal of Marketing Research*, 44(1), 114–127.
- Dawar, N. (2018). Marketing in the age of Alexa. Retrieved from <https://hbr.org/2018/05/marketing-in-the-age-of-alexa>.
- De Keyser, A., Köcher, S., Alkire, L., Verbeeck, C., & Kandampully, J. (2019). Frontline service technology infusion: Conceptual archetypes and future research directions. *Journal of Service Management*. <https://doi.org/10.1108/JOSM-03-2018-0082>.
- Delcourt, C., Gremler, D. D., De Zanet, F., & van Riel, A. C. (2017). An analysis of the interaction effect between employee technical and emotional competencies in emotionally charged service encounters. *Journal of Service Management*, 28(1), 85–106.
- Digfin (2018, October 17) How Xiao-i's robot became the voice of China's banks. Retrieved from <https://www.digfinngroup.com/xiaoi/>.
- Dion, D., & Borraz, S. (2017). Managing status: How luxury brands shape class subjectivities in the service encounter. *Journal of Marketing*, 81(5), 67–85.
- Eisend, M., & Schuchert-Güler, P. (2006). Explaining counterfeit purchases: A review and preview. *Academy of Marketing Science Review*, 1–22.
- Eli, L., Bar-Tat, Y., & Kostovetzki, I. (2001). At first glance: Social meanings of dental appearance. *Journal of Public Health Dentistry*, 61(3), 150–154.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280.
- Gabbott, M., & Hogg, G. (2001). The role of non-verbal communication in service encounters: A conceptual framework. *Journal of Marketing Management*, 17(1–2), 5–26.
- Goode, L. (2018, May 8) How Google's eerie robot phone calls hint at AI's future. Retrieved from <https://www.wired.com/story/google-duplex-phone-calls-ai-future/>.
- Grandey, A. A. (2000). Emotional regulation in the workplace: A new way to conceptualize emotional labor. *Journal of Occupational Health Psychology*, 5(1), 95.
- Grandey, A. A., Dickter, D. N., & Sin, H. (2004). The customer is not always right: Customer aggression and emotion regulation of service employees. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, 25(3), 397–418.
- Gremler, D. D., & Gwinner, K. P. (2000). Customer-employee rapport in service relationships. *Journal of Service Research*, 3(1), 82–104.
- Grougiou, V., & Pettigrew, S. (2011). Senior customers' service encounter preferences. *Journal of Service Research*, 14(4), 475–488.
- Gutek, B. A., Groth, M., & Cherry, B. (2002). Achieving service success through relationships and enhanced encounters. *Academy of Management Perspectives*, 16(4), 132–144.
- Hacker, S. (2009). *DecPositive interspecific interactions*. Chichester: eLS. John Wiley & Sons Ltd. <http://www.els.net>. <https://doi.org/10.1002/9780470015902.a0021901>.
- Hashimi, Y. (2017, April 19) How virtual agents will transform customer engagement. Retrieved from <https://www.ibm.com/blogs/insights-on-business/insurance/cognitive-virtual-agents-will-transform-customer-engagement/>.
- Hennig-Thurau, T., Groth, M., Paul, M., & Gremler, D. D. (2006). Are all smiles created equal? How emotional contagion and emotional labor affect service relationships. *Journal of Marketing*, 70(3), 58–73.
- Hertz, N., & Wiese, E. (2018). Under pressure: Examining social conformity with computer and robot groups. *Human Factors*, 60(8), 1207–1218.
- Hill, J., Ford, W. R., & Farreras, I. G. (2015). Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in Human Behavior*, 49, 245–250.
- Holzwarth, M., Janiszewski, C., & Neumann, M. M. (2006). The influence of avatars on online consumer shopping behavior. *Journal of Marketing*, 70(4), 19–36.
- Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155–172.
- Hyken, S. (2017a, June 10). Half of people who encounter artificial intelligence don't even realize it. Retrieved from <https://www.forbes.com/sites/shephyken/2017/06/10/half-of-people-who-encounter-artificial-intelligence-dont-even-realize-it/#6b6c7163745f>.
- Hyken, S. (2017b). AI and Chatbots are transforming the customer experience. July 15 <https://www.forbes.com/sites/shephyken/2017/07/15/ai-and-chatbots-are-transforming-the-customer-experience/#1cad7b5741f7>.
- iSimplify (2018). Will AI be your next contact center employee? October 8 <https://www.isimplify.com/will-ai-be-your-next-contact-center-employee/>.
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586.
- Jaworski, B. J. (2011). On managerial relevance. *Journal of Marketing*, 75(4), 211–224.
- Jones, E. E., & Harris, V. A. (1967). The attribution of attitudes. *Journal of Experimental Social Psychology*, 3(1), 1–24. [https://doi.org/10.1016/0022-1031\(67\)90034-0](https://doi.org/10.1016/0022-1031(67)90034-0).
- Kaplan, J. (2015). *Humans need not apply: A guide to wealth and work in the age of artificial intelligence*. Yale University Press.
- Kraak, J. M., Lunardo, R., Herrbach, O., & Durrieu, F. (2017). Promises to employees matter, self-identity too: Effects of psychological contract breach and older worker identity on violation and turnover intentions. *Journal of Business Research*, 70, 108–117. <https://doi.org/10.1016/j.jbusres.2016.06.015>.
- Kuokkanen, H. (2017). Fictitious consumer responsibility? Quantifying social desirability bias in corporate social responsibility surveys. *Palgrave Communications*, 3, 16106.
- Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., ... 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.
- Leary, M. R., Kelly, K. M., Cottrell, C. A., & Schreindorfer, L. S. (2013). Construct validity of the need to belong scale: Mapping the nomological network. *Journal of Personality Assessment*, 95(6), 610–624.
- Lee, Y. H., & Ching Lim, E. A. (2010). When good cheer goes unrequited: How emotional receptivity affects evaluation of expressed emotion. *Journal of Marketing Research*, 47(6), 1151–1161.
- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69–96.
- Liao, H., & Chuang, A. (2007). Transforming service employees and climate: A multilevel, multisource examination of transformational leadership in building long-term service relationships. *Journal of Applied Psychology*, 92(4), 1006.
- Lim, E. A. C., Lee, Y. H., & Foo, M. D. (2017). Frontline employees' nonverbal cues in service encounters: A double-edged sword. *Journal of the Academy of Marketing Science*, 45(5), 657–676.
- Lloyd, A. E., & Luk, S. T. (2011). Interaction behaviors leading to comfort in the service encounter. *Journal of Services Marketing*, 25(3), 176–189.
- Lomas, N. (2018). Duplex shows Google failing at ethical and creative AI design. Retrieved from <https://techcrunch.com/2018/05/10/duplex-shows-google-failing-at-ethical-and-creative-ai-design/>.
- Madrigal, A. (2018, May 8). Service workers forced to act like robots meet their match. Retrieved from <https://www.theatlantic.com/technology/archive/2018/05/humans-acting-like-robots-vs-robots-acting-like-humans/559955/>.
- Maglio, P. P. (2014). *Smart service systems*. Editorial Column6 (1), i–ii March.
- Marr, B. (2019, May 7). Artificial intelligence is creating a fake world – what does that mean for humans? Retrieved from <https://www.forbes.com/sites/bernardmarr/2019/05/07/artificial-intelligence-is-creating-a-fake-world-what-does-that-mean-for-humans/#553c777e32bf>.

- Maslach, C., Leiter, M. P., & Jackson, S. E. (2012). Making a significant difference with burnout interventions: Researcher and practitioner collaboration. *Journal of Organizational Behavior*, 33(2), 296–300.
- McCallum, J. R., & Harrison, W. (1985). *Interdependence in the service encounter. The service encounter: Managing employee/customer interaction in service businesses*. 18(4), 35–48.
- Medler-Liraz, H. (2016). The role of service relationships in employees' and customers' emotional behavior, and customer-related outcomes. *Journal of Services Marketing*, 30(4), 437–448.
- Meed, A., (2018, November 26), Google Duplex phone calls aren't doing a good job of disclosing their robotic nature. Retrieved from <https://bgr.com/2018/11/26/google-duplex-disclosure-lacking-calls/>.
- Mende, M., Scott, M., van Doorn, J., Shanks, I., & Grewal, D. (2017). Service robots rising: How humanoid robots influence service experiences and food consumption. Retrieved from <http://www.msi.edu/reports/service-robots-rising-how-humanoid-robots-influence-service-experiences-and/>.
- Meuter, M. L., Bitner, M. J., Ostrom, A. L., & Brown, S. W. (2005). Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. *Journal of Marketing*, 69(2), 61–83.
- Miyazaki, A. D., Lassar, W. M., & Taylor, K. A. (2007). Hispanic vs non-Hispanic response to online self-service tasks: Implications for perceived quality and patronage intentions. *Journal of Services Marketing*, 21(7), 520–529.
- Moon, Y. (2003). Don't blame the computer: When self-disclosure moderates the self-serving bias. *Journal of Consumer Psychology*, 13(1–2), 125–137.
- Mori, M. (2012, June) The Uncanny Valley. Retrieved from <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&number=6213238>.
- Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, 56(1), 81–103.
- NPR (2018). Google's Duplex could be your new personal assistant. December 24 <https://www.npr.org/2018/12/24/679895636/googles-duplex-could-be-your-new-personal-assistant>.
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 17(4), 460–469.
- Orth, U. R., Hoffmann, S., & Nickel, K. (2019). Moral decoupling feels good and makes buying counterfeits easy. *Journal of Business Research*, 98, 117–125.
- Ostrom, A. L., Parasuraman, A., Bowen, D. E., Patricio, L., & Voss, C. A. (2015). Service research priorities in a rapidly changing context. *Journal of Service Research*, 18(2), 127–159.
- Palmatier, R. W., Jarvis, C. B., Bechhoff, J., & Kardes, F. R. (2009). The role of customer gratitude in relationship marketing. *Journal of Marketing*, 73(5), 1–18.
- Palmer, A. (2019, January 7) Move over Furby: Japanese robot, 'Lovot,' designed to love and hug lonely humans eyes launch in the U.S. Retrieved from <https://www.dailymail.co.uk/sciencetech/article-6564113/Move-Furby-Japanese-robot-designed-love-hug-lonely-humans-eyes-launch-U-S.html>.
- Pantel, J. H., Bohan, D. A., Calcagno, V., David, P., Duyck, P. F., Kamenova, S., & Tixier, P. (2017). 14 questions for invasion in ecological networks. *Advances in ecological research*. Vol. 56. *Advances in ecological research* (pp. 293–340). Academic Press.
- Patterson, P. (2016). Retrospective: Tracking the impact of communications effectiveness on client satisfaction, trust and loyalty in professional services. *Journal of Services Marketing*, 30(5), 485–489.
- PBSI (2019, May 17). What we can learn from robot ethics. Retrieved from <http://www.pbsionthenet.net/article/133442/What-we-can-learn-from-robot-ethics.aspx>.
- Pichai, S. (2018). May 8 <https://www.youtube.com/watch?v=D5VN56jQMWM>.
- Pounders, K. R., Babin, B. J., & Close, A. G. (2015). All the same to me: Outcomes of aesthetic labor performed by frontline service providers. *Journal of the Academy of Marketing Science*, 43(6), 670–693.
- Pressman, A. (2018, May 10) Deciding whether to fear or celebrate Google's mind-blowing AI demo. Retrieved from <http://fortune.com/2018/05/10/google-duplex-ai-demo/>.
- Purdy, M., & Daugherty, P. (2017). How AI boosts industry profits and industry innovation. Retrieved from [https://www.accenture.com/t20170620T055506\\_w\\_us/en/\\_acnmedia/Accenture/next-gen-5/insight-ai-industry-growth/pdf/Accenture-AI-Industry-Growth-Full-Report.pdf?la=en](https://www.accenture.com/t20170620T055506_w_us/en/_acnmedia/Accenture/next-gen-5/insight-ai-industry-growth/pdf/Accenture-AI-Industry-Growth-Full-Report.pdf?la=en).
- Raajpoot, N. (2004). Reconceptualizing service encounter quality in a non-western context. *Journal of Service Research*, 7(2), 181–201.
- Rafaelli, A., Altman, D., Gremler, D. D., Huang, M. H., Grewal, D., Iyer, B., ... de Ruyter, K. (2017). The future of frontline research: Invited commentaries. *Journal of Service Research*, 20(1), 91–99.
- Randhawa, P., Calantone, R. J., & Voorhees, C. M. (2015). The pursuit of counterfeited luxury: An examination of the negative side effects of close consumer–brand connections. *Journal of Business Research*, 68(11), 2395–2403.
- Renda, A. (2019). *Artificial intelligence ethics, governance and policy challenges. Report of a CEPS task force*. (February 2019).
- Rust, R., & Huang, M. (2014). The service revolution and the transformation of marketing science. *Marketing Science*, 33(2), 206–221.
- Schalow, T. (2015). Mutualism and knowledge sharing in an age of advanced artificial intelligence. *European conference on knowledge management* (pp. 665). Academic Conferences International Limited September.
- Schau, H. J., & Gilly, M. C. (2003). We are what we post? Self-presentation in personal web space. *Journal of Consumer Research*, 30(3), 385–404.
- Schwab, K. (2016, January 14) The fourth industrial revolution: What it means, how to respond. Retrieved from <https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/>.
- Scott, M. L., Mende, M., & Bolton, L. E. (2013). Judging the book by its cover? How consumers decode conspicuous consumption cues in buyer–seller relationships. *Journal of Marketing Research*, 50(3), 334–347.
- Sharma, N., & Patterson, P. G. (1999). The impact of communication effectiveness and service quality on relationship commitment in consumer, professional services. *Journal of Services Marketing*, 13(2), 151–170.
- Simon, H. A. (1965). *The shape of automation for men and management*. New York, NY: Harper and Row.
- Simonite, T. (2018, October 9) Google's human-sounding phone bot comes to the pixel. Retrieved from <https://www.wired.com/story/google-duplex-pixel-smartphone/>.
- Singh, R. (2017, December 19) Introducing ivy, your new cognitive hotel concierge. Retrieved from <https://www.ibm.com/blogs/client-voices/ivy-cognitive-hotel-concierge/>.
- Sirianni, N. J., Bitner, M., Brown, S. W., & Mandel, N. (2013). Branded service encounters: Strategically aligning employee behavior with the brand positioning. *Journal of Marketing*, 77(6), 108–123.
- Söderlund, M. (2017). Employee display of burnout in the service encounter and its impact on customer satisfaction. *Journal of Retailing and Consumer Services*, 37, 168–176.
- Söderlund, M., & Rosengren, S. (2008). Revisiting the smiling service worker and customer satisfaction. *International Journal of Service Industry Management*, 19(5), 552–574.
- Solomon, M. R., Surprenant, C., Czepiel, J. A., & Gutman, E. G. (1985). A role theory perspective on dyadic interactions: The service encounter. *The Journal of Marketing*, 99–111.
- Spector, P. E. (1986). Perceived control by employees: A meta-analysis of studies concerning autonomy and participation at work. *Human Relations*, 39(11), 1005–1016.
- Taylor, K. (2018, April 10) This Mexican chain requires every worker to do one thing when they apply for a job — And it goes all the way up to the president. Retrieved from <https://www.businessinsider.com/moes-hiring-tests-welcome-to-moes-2018-4>.
- Tessitore, T., & Geuens, M. (2013). PP for 'product placement' or 'puzzled public'? The effectiveness of symbols as warnings of product placement and the moderating role of brand recall. *International Journal of Advertising*, 32(3), 419–442.
- Tessitore, T., & Geuens, M. (2019). Arming consumers against product placement: A comparison of factual and evaluative educational interventions. *Journal of Business Research*, 95, 38–48.
- The Economist (2018, March 31) Customer service could start living up to its name. Retrieved from <https://www.economist.com/special-report/2018/03/31/customer-service-could-start-living-up-to-its-name>.
- Theil, W. (2019). The role of AI in customer experience. Retrieved from <https://www.pointillist.com/blog/role-of-ai-in-customer-experience/>.
- Thompson, C. J., & Hirschman, E. C. (1995). Understanding the socialized body: A poststructuralist analysis of consumers' self-conceptions, body images, and self-care practices. *Journal of Consumer Research*, 22(2), 139–153.
- Townsend, T. (2017, April 20) Google Home can now recognize different users by their voice. Retrieved from <https://www.recode.net/2017/4/20/15364120/google-home-multiple-accounts>.
- United Nations Office on Drugs and Crime (2019). Retrieved from [https://www.unodc.org/documents/data-and-analysis/tocta/8.Counterfeit\\_products.pdf](https://www.unodc.org/documents/data-and-analysis/tocta/8.Counterfeit_products.pdf).
- Van Vaerenbergh, Y., Orsingher, C., Vermeir, I., & Larivière, B. (2014). A meta-analysis of relationships linking service failure attributions to customer outcomes. *Journal of Service Research*, 17(4), 381–398.
- Vanderbroeck, F. (2018). Travelbird sees 30% drop in average handling time as CSAT soars with Digital Genius. <https://www.digitalgenius.com/casestudy/travelbird-adopts-ai-to-refine-customer-service/>, Accessed date: 30 July 2018.
- Verhagen, T., Van Nes, J., Feldberg, F., & Van Dolen, W. (2014). Virtual customer service agents: Using social presence and personalization to shape online service encounters. *Journal of Computer-Mediated Communication*, 19(3), 529–545.
- Verhoef, P. C. (2003). Understanding the effect of customer relationship management efforts on customer retention and customer share development. *Journal of Marketing*, 67(4), 30–45.
- Verleye, K., Gemmel, P., & Rangarajan, D. (2016). Engaged customers as job resources or demands for frontline employees? *Journal of Service Theory and Practice*, 26(3), 363–383.
- Voorhees, C. M., Fombelle, P. W., Gregoire, Y., Bone, S., Gustafsson, A., Sousa, R., & Walkowiak, T. (2017). Service encounters, experiences and the customer journey: Defining the field and a call to expand our lens. *Journal of Business Research*, 79, 269–280.
- Webster, C., & Sundaram, D. S. (2009). Effect of service provider's communication style on customer satisfaction in professional services setting: The moderating role of criticality and service nature. *Journal of Services Marketing*, 23(2), 103–113.
- 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.
- Wong, S. (2018). *New Scientist*, 238(3178) ISSN: 0262 4079.
- Workplace Institute 2018 (retrieved on 2019 February 6). Can artificial intelligence make work better? Retrieved from <https://workforceinstitute.org/artificial-intelligence/>.
- Zlotowski, J., Yogeewaran, K., & Bartneck, C. (2017). Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources. *International Journal of Human-Computer Studies*, 100, 48–54.

**Stacey G. Robinson** is an Assistant Professor at the University of Alabama. Her research focuses on innovating and understanding the customer, and frontline employee experience, in retail and service exchanges. Her research has been published in the *Journal of Marketing*, *Journal of the Academy of Marketing Science*, *International Journal of Research in Marketing*, *Journal of Service Research*, *Journal of Business Research*, and has been presented at a number of international and national conferences. Stacey serves on the editorial review board for the *Journal of the Academy of Marketing Science*, *Journal of Retailing*, *Journal of Service Research*, and *Journal of Business Research*.

**Chiara Orsingher** is an Associate Professor of Marketing at the University of Bologna, Italy. Her research interests include service recovery and complaint handling, meta-analysis, referral reward programs, and customer relationship with digital helpers. Her work has appeared in the *Journal of Academy of Marketing Science*, *Academy of Management Perspectives*, *Journal of Service Research*, *Journal of Service Management*, *Journal of Business Research* and other leading journals.

**Linda Alkire** (née Nasr) is an Assistant Professor of Marketing at Texas State University (USA). She earned her PhD degree from The University of Manchester (UK). Dr. Alkire's research interests include transformative service research (TSR) and technology in service. She has published her research in a number of journals including the *Journal of Service Management*, the *Journal of Services Marketing*, *The Service Industries Journal*, among others. Dr. Alkire serves as Editorial Director of the *Journal of Service Management*, and Associate Editor for the *Journal of Services Marketing* and *The Service Industries Journal*. She is Co-Chair of AMA SERVSIG.

**Arne De Keyser** is an Assistant Professor of Marketing at EDHEC Business School (France). His research focuses on customer experience, service recovery and frontline service technology. Arne has published articles in the *Journal of Service Research*, *International Journal of Research in Marketing*, *Journal of Business Research*, *Journal of Service Management* and the *Journal of Service Theory and Practice*. He has won various research and teaching awards, including the SERVSIG Best Dissertation Award in 2015. Arne serves on the editorial boards of the *Journal of Service Research*, *Journal of Business Research*, *Journal of Service Management*, and the *Journal of Service Theory and Practice*.

**Michael Giebelhausen** is an Associate Professor of Marketing at Clemson University. He earned his Ph.D. in Marketing from the Florida State University College of Business. Professor Giebelhausen's research examines how consumers respond to self-concept threats, particularly those that occur during frontline service encounters. His ongoing

work focuses on frontline service encounters involving technologies such as artificial intelligence (AI) or robotic agents.

**K. Nadia Papamichail** is an Associate Professor in Information and Decision Systems at Alliance Manchester Business School, The University of Manchester. Her publications have appeared in books and journals including *Decision Support Systems*, *Journal of Business Research*, *Omega*, *Journal of the Operational Research Society*, *Expert Systems with Applications and Artificial Intelligence*. She has co-authored a book on 'Decision Behaviour, Analysis and Support', published by Cambridge University Press. She is Fellow of the Alan Turing Institute (the leading UK national institute for Data Science and Artificial Intelligence) and Chair of the Decision Analysis special interest group - DASIG (a network of academics and practitioners whose role is to promote Decision Analysis in the UK and abroad).

**Poja Shams** is an Assistant Professor at Karlstad Business School in Sweden. His research has primarily been focused on consumer decision making and visual attention in the retail environment. His research has been awarded by the Gunnar Sundblad Research Foundation and published in several distinguished journals such as *Journal of Business & Retail Management Research*, *Journal of Business Research* and *Psychology & Marketing*.

**Mohamed Sobhy Temerak** Mohamed Sobhy Temerak is an Associate Professor of Marketing at Faculty of Commerce, Cairo University. He earned his Ph.D. in service marketing from the University of Nottingham. Dr. Mohamed's research interests include customer education, dynamics of intercultural service encounter, complex services and customer-to-customer interactions. He has published his research in *Journal of Service Research*, *Tourism Management*, *Journal of Business Research*, *Journal of Retailing and Consumer Services* and *Journal of Financial Services Marketing*. He is a marketing research consultant with more than ten years of experience across the Middle East.