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Frontline Encounters of the AI Kind: An Extended Service Encounter Framework

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Frontline Encounters of the AI Kind: An Extended Service Encounter Framework

1. Introduction

The World Economic Forum cites artificial intelligence (AI) as the center of the world's current technological revolution. AI[1] is attributed with transforming the way people "work, live and relate to one another" (Schwab, 2016); a transformation that will no doubt extend to frontline service encounters. While traditional exchanges between human customers and human frontline employees remain commonplace, AI plays an increasing role. AI-powered employees now 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 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 that has been criticized for "fooling" the human employee. In short, AI is radically reshaping service encounters as it transforms existing interactions and enables new interactions at the service frontline.

The notion that individuals will not know whether they are dealing with AI seems particularly troubling. While early chatbots were designed to speak clear and concisely (i.e., robotically), chatbots 2.0 are programed to be "perfectly imperfect" in their imitation of humans

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[1] Artificial intelligence (AI), defined as the science of making machines do things that would require intelligence if done by a human (Minsky 1968), is used here to refer to non-human customers and employees powered by AI.

(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, 2017). Efforts to design AI agents difficult or impossible to delineate from human, 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 sorts. We advance humanlike AI creates a counterfeit service encounter, if the customer or FLE, is unaware they are interacting with a non-human partner. As AI continues to become more humanlike, opportunities for these counterfeit service encounters will only increase.

The increasing prevalence of AI-powered service encounters, suggests it provides customers and firms with some net benefit. In support of this notion, several researchers have found that such technologies can positively influence customer perceptions (Holzwarth et al., 2006; Verhagen et al., 2015). However, the extant literature does not address the impact of an AI actor, in the frontline employee (FLE) or customer role, on the service encounter. Additionally, and not surprisingly given the recent emergence of human-like AI, little research has investigated how humanlike AI, in an employee 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 can either be human or AI (see figure 1). Further, we consider the issue of whether one actor is aware that the other is an 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 extended framework will support a research agenda focused on the distinct aspects of AI-enabled 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 FLE or customer, or both FLE and customer (i.e., AI to AI). Second, we present a literature review and a research agenda for each type of service encounter identified. Lastly, we highlight the potential for counterfeit service encounters and discuss associated implications.

2. Extended Service Encounter Framework

The term "service encounter" describes an exchange between a firm and customer (Bitner, 1990; Voorhees et al., 2017), yet 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 et al., 1985 p. 101). As encounters evolve to include AI-powered actors, and research extends beyond evaluating traditional human to human service encounters, to include AI-human, and AI-AI exchanges, an evolved framework, defining the type of encounter between FLE and customer is needed. As per the extant service encounter literature, the present framework focuses exclusively on dyadic encounters. FLEs and customers participating in an exchange may be human or AI, and accordingly the axes below represent the possible actors, and each quadrant is defined based upon its composition.

----- insert Figure 1 here -----

3. Review and Research Agenda

Given the rapid advancement and usage of AI within exchanges between customer and firm, researchers and practitioners alike will benefit from guidelines on how to conceptualize encounters in which the exchange is characterized by a 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 (human customer to human FLE), **(2)** interspecific[2] AI customer (AI customer to human FLE), **(3)** interspecific AI FLE (human 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, and explicitly identify research questions that, if addressed, will advance knowledge on evolved dyadic service encounters.

3.1 Interhuman Service Encounters

The interhuman, or human to human, quadrant illustrates service encounters in which FLE and customer are both humans. 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 and Chuang, 2007). However, as AI technologies rapidly 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 customer actors, the focus of this quadrant is on how interhuman encounters may be impacted by, and/or compare to interspecific encounters.

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[2] The term interspecific is used to describe interactions between two distinct species (Hacker, 2009; Schalow, 2015; Pantel et al., 2017), such as human and AI.

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, risk perceptions, 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 and Hogg, 2001; Raajpoot, 2004; Lloyd and Luk, 2011; Patterson, 2016) may be difficult to replace with an AI actor representing 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 some services, the failure to convey empathy and care for customers may reduce customers' satisfaction (Webster and Sundaram, 2009) and AI may be an unsuitable FLE replacement. Furthermore, for emotionally charged service encounters due to service failure (Rafaeli et al., 2017) or nature of the service (Delcourt et al., 2017), a human FLE may reflect respect and appreciation for customers who might feel discomfort, insulted or offended (Dallimore et al., 2007; Rafaeli et al., 2017). The usage of an AI actor may not be ideal in these situations, despite potential efficiency gains in the exchange. 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 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 subdue interhuman encounters at an emotional level.

Some customers may also look for and care more about the social elements of service encounters rather than service itself, and AI may be an unsuitable actor (FLE or customer) replacement. Relationship-motivated customers expecting communal relationship with FLEs (Scott et al., 2013), welcome emotional expression (Lee and Lim, 2010; Lim et al., 2017), and look for non-verbal cues to reduce ambiguity (Hennig-Thurau et al., 2006; Soderlund and Rosengren, 2008; Patterson, 2016), feel comfortable (Lloyd and Luk, 2011), build trust (Gabbott and Hogg, 2001; Sharma and Patterson, 1999), and develop rapport (Medler-Liraz, 2016; Gutek et al., 2002). Although AI technologies can outperform humans in reliability and accuracy (e.g., task-related aspects) (Meuter et al., 2005), it usually lacks rich communication (Miyazaki et al., 2007) and emotion (Grougiouand & 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 able to recognize and respond to emotions may fulfill a customers' need for emotional exchanges. For professional services characterized by high information asymmetries for example (e.g., surgery), an AI-powered chatbot could be "on call" 24 hours a day responding to customer queries at any can 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 et al., 1992; Dion & Borraz, 2017; Pounders et al., 2015). In turn, customers may relate to them when engaging in purchase decisions (Argo et al., 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 where customers rely on service employees as anchors of how they will appear or feel when they use product or service. For example, Eli et al., (2001) showed the appearance of a dentist's teeth are important in forming customer perceptions of his/her professionalism and social skills. Dion & Borraz (2017) demonstrated FLEs and customers of luxurious stores look similar not only in how they are dressed 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 or customer. Although in the near future customers may use AI FLEs as anchors of how a product might affect their appearance. Future research could also examine if AI FLEs powered by deep learning can provide customers with suggestions that match their preferences and desired self. For example, would customers prefer a transactional relationship with a human FLE, or would they prefer to interact with an AI FLE that knows detailed information about the customer, such as the content of customers' wardrobe, purchase history, or preferred style?

It's 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 and Ko, 2012; Dallimore et al., 2007; Rafaeli et al., 2017), resulting in negative consequences to the FLE and firm (Grandey et al., 2004; Rafaeli et al., 2017; Soderlund, 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 (Sharma and Patterson, 1999; Lim et al., 2017). 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 a FLE with another human FLE (Beatty et al., 1996; Gutek et al., 2002) because of a shared history of interactions (Beetles and 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

While seemingly futuristic, customers may be replaced by AI in routine service encounters, as current advances in technology have made it possible for customers to utilize AI assistants to engage in exchanges with FLEs. Interspecific is used to describe interactions between two distinct species (Hacker, 2009; Schalow, 2015; Pantel et al., 2017), such as human and AI. In this section, we will discuss both potential positive and negative outcomes of interspecific service encounters - AI customer to human 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 the FLE. Early predictions (Simon, 1965) stated smart machines would be capable of replacing the human workforce, regardless of the type of work, by 1985. 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 and Rust, 2018).

However, situations in which FLEs are human and customers are replaced by 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 person on the other end knew the AI was still present (Pressman, 2018). What’s more, the technology 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. 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 et al., 2013). However, there is a downside for the FLE. Prior research has shown that surface acting decreases employee engagement and increases employee turnover. When deep acting, conversely, 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 FLE's 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 that 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 (Nass & Moon, 2000; Moon, 2003; Hertz, 2018). 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 that they know to be a machine. Treating a humanlike AI as less-than-human may induce, feelings of discomfort or dissonance (Lee, 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 (Lee, 2010; Leary et al., 2013).

Firms may 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 1,000 different people based on facial features alone (Palmer, 2019). 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 and Leone, 2003). What might be the result of allowing an FLE to customize how AI customers speak to them?

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 equal to you in terms of 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 et al., 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 et al., 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 that have traditionally positioned themselves as providers of exceptional customer service. Research is needed to see if such an effect might occur and what managerial tactics (e.g., types of employee training) might 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 their growth 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. Additionally, these encounters will likely affect the AI FLE’s human coworkers.

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 et al. (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 FLE (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? Does impolite behavior continue to occur during contiguous interhuman encounters, thereby negatively impacting the human FLE actor in future dyadic exchanges?

Mende et al. (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 attitude toward 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 et al. (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. These feelings are theorized to originate from an in-group vs. out-group distinction, where AI is considered part of an out-group that may threaten the human in-group. Following similar reasoning leads to the question of how a perceived threat to human identity affects attitudes toward the firm, or general satisfaction in spite of the level of service provided by the AI.

While AI FLE's impact on customers has gained traction in the literature, less is known about how the presence of an AI FLE affects perceptions of human FLEs. While research addresses the impact of AI FLEs replacing human FLEs, and the future of the workplace (Frey and Osborne 2017; Huang and 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 its initial impact on the human customer, and include the impact on human FLEs who may be working alongside the AI FLE. For example, imagine a guest checks into a hotel, and an 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 day or night, 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 et al. (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 et al., 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 FLE 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 that deals with 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. A firm utilizing the technology may significantly improve employee retention metrics, and customer call handling times (Vanderbroeck, 2018). Hence, improvement to the work environment, due to AI FLEs, may lead human FLEs to consider AI as true co-workers/partners and increase levels of employee engagement (Crawford et al., 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.

3.4 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 have 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-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, as they do not occur in a natural language. This happens, for example, 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. However, it would be very inefficient for AI actors in an interAI encounter to have a humanlike conversation with one another. In a more efficient scenario, the receiving AI recognizes another AI is making contact and the communication shorted in the form of code or a digital redirect.

InterAI service encounters need further investigation, and there are several pressing questions for future research, such as how consumers will react towards being excluded from the service encounter. If a customer delegates to an AI assistant and the firm responds with an AI FLE, the customer is losing control over the process perhaps in favor of convenience. This tradeoff suggests trust towards the service brand would play an even more important role than it does in interhuman or interspecific service encounters.

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 et al., 2014). In interAI service encounters, this search could be impossible or extremely difficult, resulting in negative affective reactions and profound customer dissatisfaction.

3.5 Counterfeit Service Encounters

Both interspecific encounter quadrants, with AI customers or AI FLEs, categorize two distinct present-day and near-future service encounters scenarios. Such encounters currently include AI acting on behalf of the customer in the form of a digital assistant, or firms employing AI FLEs to initiate or answer customer service calls, or text or email customers to gauge satisfaction. As previously mentioned, a notable half of customers interacting with AI FLEs were unaware their exchange partner was non-human (Hyken, 2017). 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.

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). Studies on counterfeiting often focus on deception (Eisend & Schuchert-Güler, 2006; Randhawa, Calantone, & Voorhees, 2015) and given attempts to make disembodied AI agents 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 that the AI actor is not human, are by definition counterfeit service encounters.

At the product launch for one of the recent AI assistants designed to aid customers in routine service encounters with firms, the developing 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, 2017). The AI assistant presented was indistinguishable from a human assistant, and did not disclose itself as non-human to its 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 that this type of encounter can create ancillary mistrust in subsequent unrelated interactions (Madrigal, 2018). Disclosing the presence of the AI actor in the dyad, may soon be regulated or called-for standard practice given apparent societal and ethical concerns. The IEEE technical professional association created guidelines calling for transparency (Lomas, 2018). While, UK's BSI labeled deception, whether it be intentional or unintentional, as a societal risk, and cautions such deception will negatively impact trust in the technology. 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). Concerns about trust erosion and its impact on a firm's employees and customers are fundamental when considering the impact of counterfeit service encounters. General research on the impact of undisclosed AI on unaware human exchange partners, and subsequent firm, and societal outcomes, are needed.

-----insert table 1 about here -----

4.0 Concluding Comments

The organizational frontline is facing unprecedented evolution, as AI technologies become a routine element of the service environment. This work introduces an extended framework delineating the various encounter types resulting from introducing AI at the service frontline. Specifically, we distinguished four service encounter types: interhuman (human FLE to human customer), interspecific AI customer (AI customer to human FLE), interspecific AI FLE (human 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 (see table 1). 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 need for AI transparency and potential for trust erosion. 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.

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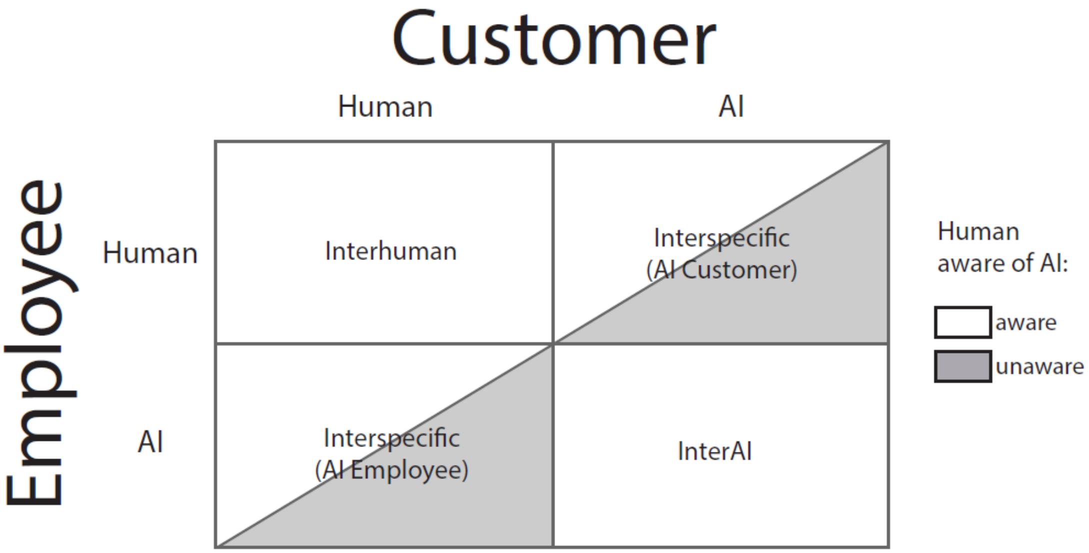
Figure 1: Extended Service Encounter Framework


Customer
Human
AI
Employee
Human
AI
Interhuman
Interspecific
(AI Customer)
Interspecific
(AI Employee)
InterAI
Human
aware of AI:
aware
unaware

Encounter Type	Research Questions
Interhuman	
High Affect	When interhuman encounter exchange partners lack empathy or are offensive to customers, do customers prefer working with AI FLEs? How might AI FLEs recognize and respond to customer emotions and fulfill their need for emotional exchange?
Information Asymmetry/ High Perceived Risk	Does expedited service via an AI FLE attenuate risk? Does an AI FLE’s ability to deliver extensive information, on demand, provide cognitive control and allow the customer to better cope with emotions?
Physical Similarity	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?
Social Connection	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 FLE replacement, and under what conditions?
Interspecific – AI Customer	
Role of emotions	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?
Customization	How does customization, with regard to AI customer-FLE exchanges, impact the human FLE?
FLE status/rank	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?
Interspecific – AI FLE	
Customer Communication	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 anti-social behavior continue to occur during contiguous interhuman, encounters and negatively impact the human actor in future dyadic exchanges? Does natural communication between AI FLE and customer improve the interaction and customer evaluations?

Threats	Do AI FLEs generate customer discomfort and threaten customer human identity perceptions?
Firm/Human FLE	Do interspecific encounters (negatively/positively) affect a firm’s human FLEs? How do interspecific encounters (negatively/positively) affect subsequent interhuman encounters, customer outcomes, and firm performance?
InterAI	
Customer Control/Trust	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?
Service Failure	Who (customer or firm) is to blame when something goes wrong as a result of interAI encounters (e.g., wrong item received)?
Counterfeit	
General	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?