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Half human, half machine – augmenting service employees with AI for interpersonal emotion regulation

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Abstract

Purpose – With the advent of increasingly sophisticated AI, the nature of work in the service frontline is changing. The next frontier is to go beyond replacing routine tasks and augmenting service employees with AI. The purpose of this paper is to investigate whether service employees augmented with AI-based emotion recognition software are more effective in interpersonal emotion regulation (IER) and whether and how IER impacts their own affective well-being.

Design/methodology/approach – For the underlying study, an AI-based emotion recognition software was developed in order to assist service employees in managing customer emotions. A field study based on 2,459 call center service interactions assessed the effectiveness of the AI in augmenting service employees for IER and the immediate downstream consequences for well-being relevant outcomes.

Findings – Augmenting service employees with AI significantly improved their IER activities. Employees in the AI (vs control) condition were significantly more effective in regulating customer emotions. IER goal attainment, in turn, mediated the effect on employee affective well-being. Perceived stress related to exposure to the AI augmentation acted as a competing mediator.

Practical implications – Service firms can benefit from state-of-the-art AI technology by focusing on its capacity to augment rather than merely replacing employees. Furthermore, signaling IER goal attainment with the help of technology may provide uplifting consequences for service employee affective well-being.

Originality/value – The present study is among the first to empirically test the introduction of an AI-fueled technology to augment service employees in handling customer emotions. This paper further complements the

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literature by investigating IER in a real-life setting and by uncovering goal attainment as a new mechanism underlying the effect of IER on the well-being of the sender.

Keywords Artificial intelligence, Customer service interactions, Interpersonal emotion regulation goal attainment, Affective well-being, Augmented service employees, Voice emotion recognition

Paper type Research paper

> The machine has no feelings, it feels no fear and no hope [...], it operates according to the pure logic of probability. For this reason I assert that the robot perceives more accurately than man. Max Frisch (1994) "Homo Faber", p. 84, Houghton Mifflin Harcourt

Introduction

Artificial intelligence (AI) is at the forefront of revolutionizing the marketplace. Particularly, the organizational frontline is undergoing significant transformation (Van Doorn *et al.*, 2017; Wirtz *et al.*, 2018). Increasingly, routine tasks are taken over by intelligent systems that allow time and cost savings. Examples include chatbots helping answer frequently occurring customer requests and intelligent phone routing systems directing customers to the respective department. The first service robots take over simple tasks as first soldiers in customer interactions (e.g. Pizza Hut), and smart algorithms are used to derive business intelligence and personalized advertising and offerings (e.g. McDonald's). The sophistication of AI systems has surpassed human cognitive capacities (e.g. Watson), and as a consequence, the predominant perspective on the integration of AI in service lies on efficiency gains and the replacement of human service employees (Huang and Rust, 2018). However, AI also has a potential to help resolve the fundamental struggle between service effectiveness and efficiency by promoting human–technology integration (Marinova *et al.*, 2017; Wilson and Daugherty, 2018), where AI augments rather than replaces service employees, such that human and AI collaboratively provide a service (Davenport *et al.*, 2009; Larivière *et al.*, 2017; Van Doorn *et al.*, 2017). Such a symbiosis could contribute to increased effectiveness and eventually lead to service productivity gains.

Reflecting the essence of the opening quote, the final frontier for AI, and with it, a particularly promising avenue for augmenting service employees lies in the empathic assistance of human service employees (Huang and Rust, 2018). Just as asserted in Homo Faber, state-of-the-art technology is catching up with the human ability to perceive emotions (e.g. Affectiva) and may soon also perceive emotions more accurately than humans. Emotions reflect the essence of human nature (Haslam, 2006) and they lie at the heart of customer service (Mattila and Enz, 2002). An important defining characteristic of service work is the requirement to perceive, regulate and express emotions (Rafaeli and Sutton, 1987). Across service industries, display rules dictate the emotion regulation requirements of service employees (Grandey, 2000; Totterdell and Holman, 2003). On the one hand, this is beneficial for the customer service experience and eventually the firm bottom line (e.g. Menon and Dubé, 2000). On the other hand, emotion regulation is one of the biggest job stressors with negative health consequences for service employees (Grandey *et al.*, 2004). This suggests that there is significant potential for integrating an intelligent system in the organizational service environment that supports employees in fulfilling their emotion regulation requirements.

The underlying research explores this potential by testing an AI emotion recognition assistant that was designed to support service employees in recognizing and regulating customer emotions in call center service interactions and makes at least three essential contributions.

First, it contributes to service management and practice as one of the first studies to empirically test the consequences of augmenting service employees with AI in an integrative, real-time fashion. It further extends previous service literature that has identified a void of research on value cocreation in the customer–service provider interface (e.g. Kaartemo and Helkkula, 2018). Second, this research contributes to the body of literature on interpersonal emotion regulation (IER). While a plethora of research has investigated the effects of *intra*personal emotion regulation, where a person regulates one's own emotions (e.g. Grandey, 2000, 2003), more recently also the phenomenon of *IER*, where a person (i.e. a sender) regulates the emotions of someone else (i.e. a target), has gained some attention (e.g. López-Pérez *et al.*, 2017; Netzer *et al.*, 2015). However, findings on the immediate consequences of IER on the sender are sparse, mainly based on role plays, and with inconsistent results (Martínez-Íñigo *et al.*, 2015; Martínez-Íñigo *et al.*, 2013; Niven, 2012). The underlying study aims to uncover the actual immediate consequences of IER on the sender in a real-life service setting. Third, to the best of our knowledge, no study so far has investigated IER goal attainment as an underlying mechanism for the consequences of IER on affective well-being.

Against this background, the underlying study discusses the results of a field study in order to investigate three main questions: (1) Can augmenting service employees with AI help employees in IER? (2) What are the immediate downstream effects of IER for customer service employees in a field context? and (3) Can IER goal attainment explain the effect of IER on service employee affective well-being?

The rest of the paper is organized as follows. First, the authors recapitulate the literature streams on AI in service management, on the role and effect of emotions and emotion regulation in service interactions and on IER and put forward their hypotheses. Subsequently, the results of a large-scale field study of augmenting service employees with AI in a call center context are reported and implications for theory and practice are discussed.

AI in service

The service industry is about to undergo a major revolution, driven by the infusion of AI (Rust and Huang, 2014). We adopt the definition of AI from Kaplan and Haenlein (2019, p. 17) "as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." The combination of data availability and sophisticated AI algorithms offers countless possibilities to curb the productivity of service operations. One example is the use of wearable devices such as smart glasses in a customer relationship management context to produce up- and cross-selling opportunities (Marinova *et al.*, 2017). This development is particularly pronounced and visible in the organizational frontline, which is also referred to as Service Encounter 2.0 (Larivière *et al.*, 2017). A prominent example of such an AI-fueled frontline service technology is chatbots. A large diversity of service firms including Lyft, Whole Foods and Spotify have integrated chatbots as an efficient, real-time customer interface. In a brick and mortar environment, the first service robots are deployed as the organizational spearhead for greeting and taking orders at global players such as Pizza Hut (Choudhury, 2016). Replacing routine service tasks that traditionally were performed by a first line of human service employees saves costs and contributes to operational efficiency.

At the other end of the spectrum, AI-based technologies have the potential to augment rather than substitute service employees (Davenport *et al.*, 2019; Marinova *et al.*, 2017). Examples again include service robots, however, then in a more collaborative fashion, such as supporting, rather than replacing human service employees in elderly care, healthcare and hospitality services (Van Doorn *et al.*, 2017). As a consequence, fewer employees may be necessary to perform the service, also producing efficiency gains. However, first and foremost augmenting employees by creating a symbiosis of human and AI in the service encounter is expected to yield effectiveness improvements, such as increasing sales and customer satisfaction (Ahearne *et al.*, 2008; Davenport *et al.*, 2019; Marinova *et al.*, 2017). While even the service employee in its traditional sense is expected to survive for the foreseeable future (Larivière *et al.*, 2017) with the advent of state-of-the-art AI, the human element may experience a kind of renaissance: "While AI will radically alter how work gets done and who does it, the technology's larger impact will be in complementing and augmenting human capabilities, not replacing them" (Wilson and

Daugherty, 2018, p. 4). There is a great potential for AI supporting firms in general and frontline employees in particular to outperform competition through service excellence, rather than to simply streamline processes and cut costs by replacing employees entirely.

Emotions in service interactions

Emotion constitutes the essence of human nature (Haslam, 2006), and social perception is directly related to emotion (Fiske *et al.*, 2007). Human service encounters are nothing else but social interactions in a commercial setting (Czepiel, 1990), and hence, emotions are omnipresent in customer service interactions. While emotions are only short lived, their duration of effect may extend far beyond the interaction. For instance, in a service recovery process, both customers' short-term complaint behavior and their long-term loyalty are a function of customer emotions (DeWitt *et al.*, 2008; Tronvoll, 2011). Likewise, negative emotions in a service encounter may lead to negative generalizations about the service provider as well as its employees and future encounters (Porath *et al.*, 2010).

Also on an interpersonal level, emotions have a dynamic effect on the direct interaction between customers and employees, where customers' affective states and their perceptions of the service are directly influenced by employee emotion displays (Pugh, 2001). Service encounters are prone to a variety of negative customer emotion expressions with deleterious consequences for service employees, including behavioral disengagement (Goussinsky, 2012), emotional exhaustion (Kern and Grandey, 2009), underperformance and withdrawal behavior (Sliter *et al.*, 2012). However, the consequences of emotions in an interaction are not unidirectional. Emotions occur in cycles of reciprocity between sender and receiver (Hareli and Rafaeli, 2008; Liu *et al.*, 2019). Though undesirable from a firm's perspective, employees may perceive and even express negative emotions toward customers in return (Walker *et al.*, 2014, 2017). Yet, organizational display rules in the service industry prescribe frontline employees how to react to customers and what emotions they are expected to suppress (Grandey *et al.*, 2010).

Emotion regulation in service interactions

Emotion regulation is a defining requirement of service jobs (Grandey, 2003). Accordingly, the effect of emotions in service interactions and the resulting job requirements for service employees discussed in the previous section can be categorized into two factors. First, employees are required to manage their own emotions (e.g. displaying positive emotions while feeling negative emotions due to the current or preceding service interaction). This form of emotion regulation is referred to as *intrapersonal* emotion regulation (Tamir, 2011). A plethora of research has documented the undesirable effects of service employees being required to regulate one's own emotions, such as work strain, fatigue, stress and burnout (Beal *et al.*, 2013; Maslach *et al.*, 2001).

Second, employees need to manage the emotions of the customer in order to achieve customer-based outcomes that lie in the best interest of the organization (e.g. soothing customer anger and turning the interaction into a satisfactory encounter). This form of emotion regulation is referred to as *interpersonal* emotion regulation (IER) (Tamir, 2011). The single most important discriminating characteristic of interpersonal (vs intrapersonal) emotion regulation is that it has a social target (Niven, 2017). That is, the sender's goal is to alter the emotional state of another person, rather than to regulate the emotions of the self. Since frontline service interactions are inherently social interactions between two people, emotion regulation is often motivated by the receiver's response and as such of interpersonal nature (Coté, 2005). While research on IER has gained some traction in the field of psychology (e.g. López-Pérez *et al.*, 2017; Niven, 2017; Tamir, 2011; Zaki and Williams, 2013), service research has a lot to add to this research stream. Translated to a service context, the sender is the frontline employee as he or she is required to regulate the emotions of the customer, who is the receiver. Surprisingly, despite the clear relevance of IER in service interactions, service research remains mute about its processes and consequences in customer–employee interactions.

In line with organizational service research that is documenting the adverse consequences of frontline service work, first attempts to isolate the effects of the IER requirement of service employees produce similarly detrimental results (Niven, 2017). For instance, Martínez-Íñigo *et al.*, (2013) document an emotionally exhausting effect of two friends engaging in positive IER in a role play. They further report survey results from a healthcare context, suggesting that negative but not positive IER may be associated with emotional exhaustion half a year later. Martínez-Íñigo *et al.* (2015) complement these findings with another role play, documenting a relatively more exhausting effect of engaging in negative versus positive IER. They note a relation between the IER strategy applied and the feedback of the receiver on the sender's emotional exhaustion. Niven *et al.* (2012), on the other hand, report results suggesting relative effects on the sender's subjective well-being that are in line with the valence of the IER strategy applied (i.e. relatively more positive effects of engaging in positive vs negative IER and vice versa). Yet, to the best of our knowledge, no study so far has comprehensively investigated the immediate net effect of IER activity on employee affective well-being in the field, considering IER success as perceived by the sender.

As a social process, attempting to regulate another person's emotions is dynamically guided by the emotion display of the target (Zaki and Williams, 2013). Its components mainly consist of perceiving and altering the target's emotional state. Via a feedback loop the sender again evaluates the emotional state of the target to receive feedback on the emotion regulation success. Translated to a customer service context, this implies that service employees, next to fulfilling a customer's request, need to constantly monitor signs of the customer hinting at changes in their emotional state and react accordingly. This requirement is even more pronounced and potentially considerably more effortful when the employee can only rely on the customer's voice as a cue. An AI-based technology that augments the employee by supporting the perception of customer emotions should hence be beneficial for IER goal attainment. A lower requirement to recognize customer emotions should free resources for the actual IER process. The resulting hypotheses are depicted in Figure 1. Formally;

H1A. Augmenting service employees with an AI-based emotion recognition technology (vs no supporting technology) will increase their IER goal attainment.

H1B. This effect will be mediated by increased IER activity.

The sender's goal attainment of the emotion regulation attempt, as reflected in the target's emotion feedback, is an important element of the emotion regulation process (Zaki and Williams, 2013). The extant psychology literature documents positive effects of such goal attainment on long-term subjective well-being (Diener *et al.*, 1999; Ryan and Deci, 2001). Goal attainment in the daily work context is associated with a positive effect on affective well-

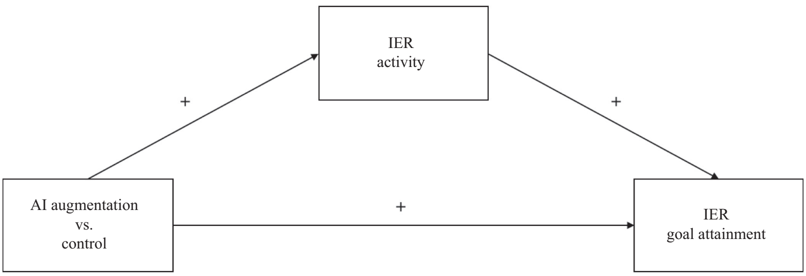


Figure 1.
Theoretical model representing H1A and H1B

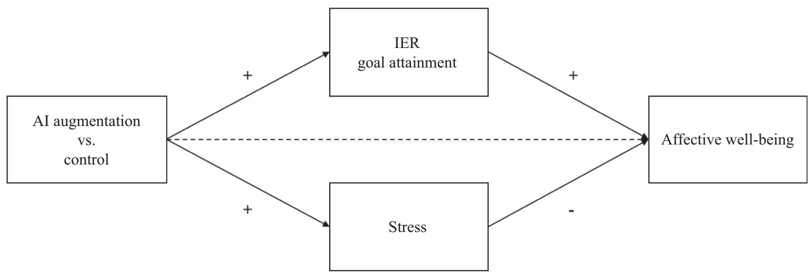
being (Harris *et al.*, 2003). Also, prior studies on intrapersonal emotion regulation have allotted success (vs failure) an important role in the effects it has on well-being outcomes (Etkin *et al.*, 2015; Gross and John, 2003). Particularly, Wong *et al.* (2017) found that successful goal attainment of regulating one's own emotions is positively related with immediate short-term effects on well-being. However, research in the domain of IER has remained largely mute about the role of emotion regulation goal attainment on well-being related outcomes for the sender.

Customer service is a goal-fulfilling process, as service employees rely on customer emotional reactions to measure their performance (Baranik *et al.*, 2017; Diefendorff and Gosserand, 2003). Thus, the emotions displayed by the customer signify to the employee whether or not he or she obtained the goal of regulating the emotions as intended. According to affective events theory (Weiss and Cropanzano, 1996), goal attainment represents a work-related event that has an immediate positive effect on well-being. Goal failure, on the other hand, is considered to result in negative well-being outcomes (Ohly and Schmitt, 2015). Hence, assisting service employees with an AI that supports their IER activities should be associated with a positive consequence on momentary well-being due to the positive effect of goal attainment.

Yet, rather than relying on themselves, AI-augmented employees are guided by the intelligent technology in recognizing customer emotions and assessing goal attainment. As a consequence, the integration of this new technology may bring about new challenges requiring service employees to adapt (Kaplan and Haenlein, 2019). Particularly, the introduction of a new technology is associated with additional work stress (Ayyagari *et al.*, 2011). This heightened level of stress may, in turn, counteract the benefits of the AI technology during the introductory phase and in turn evoke negative implications performance and well-being related consequences (Jackson and Schuler, 1985). Therefore, until the AI technology is established in the specific work environment, the introduction of an emotion recognition AI may also have a negative effect on momentary well-being via increased levels of stress. A model summarizing our main theoretical predictions following the resulting additional hypotheses is depicted in Figure 2. Formally,

H2A. Augmenting service employees with an emotion recognition AI will positively impact their momentary affective states through perceived goal attainment.

H2B. Augmenting service employees with an emotion recognition AI will negatively impact their momentary affective states through increased levels of perceived stress.



Note(s): The upper path, associating AI augmentation with a positive effect on affective well-being represents *H2A*, the lower path, depicting the negative effect on affective well-being through increased levels of stress, represents *H2B*

Figure 2.
Main theoretical model representing H2A and H2B

Method

For the study context, we relied on the financial service industry. Financial services oftentimes are emotionally laden and emotions play a dominant role in financial decision-making (De Martino *et al.*, 2006; Lee and Andrade, 2011). These attributes make the financial services sector ill-suited for relying entirely on frontline employee-replacing (FLE) AI solutions (Shell and Buell, 2019). Thus, related customer service interactions provide an ideal setting for the underlying study. This was also resembled in the call centers taking part in the study; interviews with higher management prior to the study revealed that recognizing and regulating customer emotions is a particular focus of employee training and the single most important task in customer service interactions. A tool supporting employees in their emotion work would thus offer potential in facilitating their work.

Underlying AI technology

An AI emotion recognition software was developed based on deep learning (LeCun *et al.*, 2015) and attention-based long short-term memory (LSTM) recurrent neural networks (Hochreiter and Schmidhuber, 1997; Wetering *et al.*, 2019), analyzing the current customer emotion from a set of six basic emotions on a rolling basis in 3-s intervals (i.e. anger, fear, happiness, surprise, disgust, sadness and neutral; Ekman *et al.*, 2013). The software was connected to the incoming audio line of customer calls at designated call center work stations and provided real-time emotion feedback to service agents in 3-s intervals. The graphical user interface displayed the current customer emotion in the form of seven emoticons. No recommendation or intervention was built into the widget that was displayed to agents on their screens.

For the training of the algorithm, 30 emotion coding experts assigned one emotion category (or neutral, when no clear category was discernible) to each subsequent 3-s interaction snippet of more than 360 customer service interactions, creating around 28,000 individual codes. All experts possessed years of relevant emotion recognition experience as part of call center service work. To further increase the precision of their annotations, expert coders listened to each conversation from beginning to end, such that they also had context. The final trained algorithm provided feedback with a level of accuracy when compared to a hold-out sample of 30% of customer service interactions (average recall = 0.67, average precision = 0.67), calculated based on standard procedures within the field of computer science (Sokolova and Lapalme, 2009). That is, the probability to detect all occurrences of a particular type of emotion in a conversation, irrespective of their subtleness, amounted to 67%, and the probability to predict the correct emotion, irrespective of their subtleness, also amounted to 67%. In comparison, the average layperson's ability to correctly categorize emotions from speech in isolation (i.e. without context) is in the range of 56-64% (Pell *et al.*, 2009). However, the benefits of the emotion recognition are likely to be much higher in a real-life context, where the expression of emotion happens in context and in relative terms, as service employees are also required to deploy their mental resources for tasks other than emotion recognition (e.g. finding a solution to a customer's problem) (Zapf *et al.*, 2003).

Procedures

Two pension funds in the Netherlands provided access to their centralized call center operations. About 24 flexible work stations, out of which 12 work stations were equipped with the AI emotion regulation support tool, were assessed for a period of four weeks. In total, 40 service employees participated in the study (20 per condition) taking 2,459 independent calls (1,206 calls in the control condition, and 1,253 calls in the AI condition). Employees were randomly assigned to condition by the call center manager. However, working at the prepared work stations and hence participation in the study was voluntary.

After each call, the following measures were taken. Before logging their job-related call details, employees filled in a short questionnaire relating to the emotion element of the call as well as their stress level (see Table 1). In particular, employees were prompted to indicate the dominant customer emotion at the beginning as well as at the end of the call, assessed according to the algorithm underlying the artificially intelligent emotion feedback tool (anger, fear, happiness, surprise, disgust, sadness and neutral when none of the basic emotions could be identified; Ekman *et al.*, 2013). Employees also indicated the degree of IER activity and IER goal attainment (both adapted from Wong *et al.*, 2017), perceived stress during the call (Grandey *et al.*, 2004) and affective well-being during the call (adapted from Kahneman *et al.*, 2004).

In addition to the self-assessed, subjective IER goal attainment measure, we computed the actual change of emotions indicated at the beginning and at the end of each conversation, respectively. When a negative (i.e. fear, sadness, anger, disgust) or neutral (i.e. surprise, neutral) emotion at the beginning of a call was attenuated/turned around toward the end of the call, inferred IER goal attainment was coded as positive, and when a positive (i.e. happiness) or neutral emotion at the beginning of a call was dampened/turned around toward the end of a call, inferred IER goal attainment was coded as zero. This inferred measure served as a form of robustness check for IER goal attainment.

As filling in a questionnaire after each call intervenes with regular business operations, the questionnaire was kept brief and contained single-item measures. While the use of single-item measures in the field is customary, previous research has shown that they perform equally well as multiple-item measures for many marketing constructs (Bergkvist and Rossiter, 2007). All measures were assessed on seven-point anchored scales.

Results

In a preliminary step, we conducted mean comparisons on the basis of independent samples *t*-tests. We then commenced with multilevel mediation analyses in order to assess the individual effect of service interactions on IER outcomes.

Variable	Mean (SD)
Emotion regulation	
Perceived emotion t_0	
What was the dominant emotion the customer displayed at the beginning of the call?	N/A
Perceived emotion t_1	
What was the dominant emotion the customer displayed at the end of the call?	N/A
IER activity	
How much did you try to change the customer's emotions?	4.05 (2.19)
IER goal attainment	
To what extent do you think you succeeded in changing the customer's emotions?	4.51 (2.15)
Employee outcomes	
Perceived stress	
How stressful did you perceive the call?	1.50 (0.99)
Affective well-being	
How did you feel during the call?	5.99 (1.39)

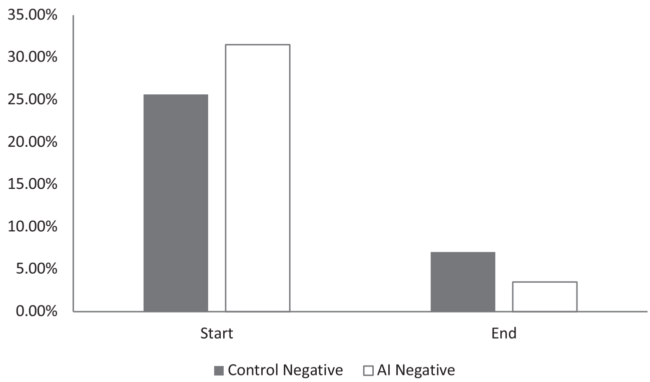
Note(s): All items were assessed on seven-point Likert scales (1 = *Not at all*, 7 = *Very much*), except for perceived emotion, which was anchored (1 = *Very negative*, 7 = *Very positive*). The categorical measure of emotion perception provided seven categories (six basic emotions after Ekman *et al.*, 2013; plus neutral)

Table 1.
Overview of study measures

Descriptives

The underlying data set comprises 2,459 independent calls taken by 40 different service employees: 1,206 calls in the control condition, and 1,253 calls in the AI condition. Calls started with a variety of customer emotions: 404 fear (16.4%), 281 surprise (11.4%), 139 anger (5.7%), 117 disgust (4.7%), 82 happiness (3.3%), 44 sadness (1.8%). About half of the calls (56.6%) were labeled to start without a particular emotion. Taken together, 3.3% of calls started clearly positive (happiness), while 28.6% (fear, sadness, anger, disgust) started clearly negative. Surprise cannot be attributed a clear valence, as it could relate to both positive (e.g. exceeding expectations) and negative surprise (e.g. falling short of expectations). This distribution was shifted considerably toward the end of each call. Here, the following emotions were present: 1,383 happiness (56.2%), 80 surprise (3.3%), 44 disgust (1.8%), 42 sadness (1.7%), 25 fear (1.0%), 18 anger (0.7%) and 867 neutral (35.3%). Thus, the ratio of positive versus negative emotions was considerably higher at the end of the calls (1,072.09%) than at the beginning (11.65%). Overall, this speaks for the effectiveness of the service employees and their ability to positively regulate customer emotions.

Breaking down the percentage of positively and negatively valenced emotions at the beginning and end of the interactions, respectively, the data already suggested a positive effect of augmenting service employees with the emotion recognition AI. As depicted in Figure 3, it appears that the emotionality of customer calls was not completely evenly distributed across conditions. With a considerably larger sample size, we would expect these figures to regress to the mean. Yet, despite having to deal with a nominally larger share of negative emotions at the beginning of the interactions ($M_{\text{Control}} = 25.6\%$ vs $M_{\text{AI}} = 31.5\%$), the share of customers that employees released with negative emotions was lower for agents in the AI condition than for those in the control condition ($M_{\text{Control}} = 18.1\%$ vs $M_{\text{AI}} = 8.4\%$). For exploratory purposes, we conducted a mixed ANOVA with condition as between-subjects factor and effect-coded emotion valence at the beginning versus end of a call for only those calls starting with a negative emotion as within factor. Results show a significant interaction effect ($F_{(1,702)} = 15.26$, $p < 0.001$), hinting at the possibility that at least for these most challenging calls from an IER perspective, FLE in the AI condition was more successful at regulating customer emotions. In the following section we will formally test our hypotheses among the entire sample of calls.



Note(s): The graphs displayed in this figure depict the collapsed percentage of negative emotions (i.e., anger, disgust, sadness and fear) at the beginning and end of each conversation, respectively

Figure 3. Transformation of negative emotions across conditions

AI and service employee effectiveness

H1 predicted that augmenting service employees with the emotion recognition AI would (1) make them more successful at regulating customer emotions and (2) free resources to regulate customer emotions. In a preliminary analysis, a correlation analysis produced significant effects in line with our hypotheses (Table 2). Independent samples *t*-tests revealed significant differences for IER activity ($M_{\text{Control}} = 3.19$, $SD_{\text{Control}} = 1.95$ vs $M_{\text{AI}} = 4.87$, $SD_{\text{Control}} = 2.09$, $t_{(2,452)} = -20.61$, $p < 0.001$), subjective (i.e. self-assessed) IER goal attainment ($M_{\text{Control}} = 3.89$, $SD_{\text{Control}} = 2.19$ vs $M_{\text{AI}} = 5.12$, $SD_{\text{Control}} = 1.93$, $t_{(2,394)} = -14.81$, $p < 0.001$) and inferred (i.e. actual change from annotation of beginning vs end of call) IER goal attainment ($M_{\text{Control}} = 0.58$, $SD_{\text{Control}} = 0.49$ vs $M_{\text{AI}} = 0.67$, $SD_{\text{Control}} = 0.47$, $t_{(2,437)} = -4.79$, $p < 0.001$). These results suggest that service employees in the AI condition showed a higher IER activity and that they were more successful at IER, offering support for H1A and preliminary support for H1B. In order to formally test H1B, we conducted a multilevel mediation model with Monte Carlo simulation (Rockwood and Hayes, 2017; Zhang *et al.*, 2009) with condition as the independent variable, IER activity as a mediator and IER goal attainment as the outcome variable. In support of mediation, the procedure revealed a significant indirect effect of condition on goal attainment via IER activity as depicted in Table 3.

As a robustness check of H1B, we also performed a moderation analysis based on logistic regression (Hayes, 2018), with IER activity as moderator and effect-coded customer emotions (i.e. 1 = positive, −1 = negative) at the beginning and end of each call as independent and dependent measures, respectively. The purpose of this analysis was to corroborate that IER goal attainment could indeed be attributed to increased IER activity and that service employees' subjective assessments of goal attainment were in line with inferred goal attainment. The model produced positive and significant main effects for emotion at the start of the call ($b = 1.94$, $\text{LLCI}_{0.95} = 1.51$, $\text{ULCI}_{0.95} = 2.37$) and IER activity ($b = 0.21$, $\text{LLCI}_{0.95} = 0.11$, $\text{ULCI}_{0.95} = 0.31$) as well as a negative significant interaction effect ($b = -0.22$, $\text{LLCI}_{0.95} = -0.32$, $\text{ULCI}_{0.95} = -0.12$). These results offer further support for the previous findings and are inherently consistent. Customers who expressed positive emotions at the beginning of a call were more likely to also end the call in a positive mood. Employee efforts to regulate customer emotions were also contributing to more positive customer emotions at the end of the call. The negative interaction effect is also intuitive, as service employees are expected to only upregulate customer emotions, hence, turning negative customer emotions into positive emotions.

AI and service employee affective well-being

H2 predicted a mixed effect of augmenting service employees with AI on their affective well-being; (1) positively via perceived goal attainment and (2) negatively via increased levels of perceived stress. In line with these predictions, complementary to the positive effect on perceived goal attainment as tested in H1A, a preliminary analysis based on an independent

	Condition	IER	Stress	Goal attainment	Well-being
Condition	1.00				
IER	0.384**	1.00			
Stress	0.084**	–0.036	1.00		
Goal attainment	0.287**	0.618**	–0.140**	1.00	
Well-being	–0.006	0.191**	–0.386**	0.328**	1.00

Note(s): $^{**}p < 0.01$

Table 2.
Correlations

	DV: IER activity 95% CI			DV: IER goal attainment 95% CI		
	b	LL	UL	b	LL	UL
Within eff						
Constant	3.19***	3.08	3.31	1.99***	0.96	3.03
IER				0.69***	0.65	0.73
Between eff						
Condition	1.68***	1.52	1.84	0.31	−0.38	1.00
IER				0.60***	0.35	0.85
Indirect eff						
IER				1.0***	0.60	1.44

Note(s): N for Level 1 (service interactions) = 2,459; N for Level 2 (service employees) = 40. CI = Monte Carlo confidence interval; LL = lower limit; UL = upper limit; $^{***}p < 0.001$

Table 3. Multilevel models predicting IER activity and IER goal attainment

samples t-test produced a significant and positive effect of condition on perceived stress ($M_{\text{Control}} = 1.42$, $\text{SD}_{\text{Control}} = 0.96$ vs $M_{\text{AI}} = 1.58$, $\text{SD}_{\text{Control}} = 1.01$, $t_{(2,455)} = -4.16$, $p < 0.001$). The direct effect on affective well-being was not significant ($M_{\text{Control}} = 6.00$, $\text{SD}_{\text{Control}} = 1.40$ vs $M_{\text{AI}} = 5.98$, $\text{SD}_{\text{Control}} = 1.37$, $t_{(2,449)} = 0.30$, $p = 0.77$). In order to formally test H2A and H2B, we conducted a multilevel parallel mediation model with Monte Carlo simulation (Rockwood and Hayes, 2017; Zhang *et al.*, 2009) with condition as the independent variable, IER goal attainment and employees stress as parallel mediators and affective well-being as the outcome variable. Results are depicted in Table 4 and support competing mediation as predicted in H2A and H2B. These results suggest that employee affective well-being is influenced by two competing processes. In support of H2A, a higher level of goal attainment boosts affective well-being, while increased stress levels related to dealing with the new AI technology decreased affective well-being in support of H2B.

Discussion

Infusing AI into the organizational frontline and understanding the dynamics and consequences of emotions in service interactions are among the two most timely and pressing topics in frontline service research (Rafaeli *et al.*, 2017). We integrate these two

	DV: Stress 95% CI			DV: IER goal attainment 95% CI			DV: Well-being 95% CI		
	b	LL	UL	b	LL	UL	b	LL	UL
Within eff									
Constant	1.42***	1.36	1.47	3.89***	3.78	4.00	6.09***	4.86	7.31
Stress							−0.30***	−0.35	−0.26
Goal							0.13***	0.10	0.15
Between eff									
Condition	0.16***	0.09	0.24	1.23***	1.07	1.40	−0.17	−0.67	0.33
Stress							−0.71**	−1.14	−0.28
Goal							0.22*	0.03	0.41
Indirect eff									
Stress							−0.12*	−0.22	−0.04
Goal							0.27*	0.04	0.51

Note(s): N for Level 1 (service interactions) = 2,459; N for Level 2 (service employees) = 40. CI = Monte Carlo confidence interval; LL = lower limit; UL = upper limit; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4. Multilevel models predicting IER goal attainment, stress and well-being

domains by investigating the consequences of augmenting service employees with an AI-based emotion recognition technology on service interaction effectiveness and affective well-being in a call center service context. In a field study based on 2,459 customer service interactions, we find that augmenting service employees with an AI emotion recognition tool can improve their effectiveness in regulating customer emotions, but may elevate stress levels at least in the introductory phase of the technology, and engaging in IER may immediately contribute to service employee well-being via a heightened sense of goal attainment.

This study extends frontline service research in at least three important ways. First, it is among the first studies to document the effects of augmenting service employees with AI during actual real-time customer interactions. It is hence directly responding to recent calls for future research revolving around AI technology and the human–technology mix in the design of the service Encounter 2.0 (Larivière *et al.*, 2017) and effective ways to integrate technology in the organizational frontline (Wirtz *et al.*, 2018). Specifically, it is one of the first empirical investigations of integrating AI in a customer/technology-assisted FLE encounter (De Keyser *et al.*, 2019). Empirical research on the effects of integrating information technology (IT) in customer service interactions is sparse. Generally, equipping service employees with IT has been demonstrated to have positive potential (e.g. improve sales performance; Ahearne *et al.*, 2008), at least as long as it is not salient to customers (Wu *et al.*, 2015). Our results show that extending service employees with AI can also support them in more traditionally human tasks and to create value for both the customer and the service employee. Taken together, the findings suggest that AI technology has the potential to play a big role in future service interactions. However, rather than entirely automating firm–customer interactions, a significant contribution of AI might be its ability to augment rather than substitute human service employees (Davenport *et al.*, 2019; Marinova *et al.*, 2017; Wilson and Daugherty, 2018). Our study demonstrates how AI-based augmentation of employees can be achieved in a customer emotion regulation context in order to increase the effectiveness of employees and improve customer interactions. At the same time, augmenting employees with an AI-based technology implies role changes and additional stress at least in the introductory phase until employees have fully integrated it into their routine (Larivière *et al.*, 2017).

Second, our field study offers ecological validity to the domain of IER (e.g. López-Pérez *et al.*, 2017; Netzer *et al.*, 2015). So far, most studies on IER are either conceptual in nature (e.g. Niven, 2017; Zaki and Williams, 2013) or investigate the underlying mechanisms and consequences in controlled laboratory environments (e.g. López-Pérez *et al.*, 2017; Martínez-Íñigo *et al.*, 2013; Netzer *et al.*, 2015; Tamir, 2011). The few exceptions that do investigate interpersonal regulation in the field are of exploratory nature and do not follow an experimental paradigm (e.g. Locke, 1996; Niven *et al.*, 2012). Our study complements this body of work by demonstrating the immediate relevance of IER in a customer service context and by documenting process evidence for how IER affects the sender's well-being in a real-life organizational setting. Importantly, in contrast to previous role play studies (e.g. Martínez-Íñigo *et al.*, 2013; Martínez-Íñigo *et al.*, 2015), we demonstrate *positive* immediate effects of IER on the sender's affective well-being during actual customer service interactions.

Third, our study proposes and tests a new underlying mechanism for the relationship of IER and employee affective well-being. It is an essential task of service employees to regulate customer emotions, yet prior studies have neglected the role of IER goal attainment on the sender. It is vital to understand how the dynamics of an interaction determine the consequences for the sender, particularly in a customer service context. Niven (2012) suggests an isolated effect of IER on affective well-being, without taking the interpersonal dynamics of an interaction into account. In line with previous studies suggesting that the valence of the target's feedback may exacerbate or buffer the negative consequences of IER on resource depletion (Martínez-Íñigo *et al.*, 2013; Martínez-Íñigo *et al.*, 2015), we hypothesized that IER consequences on the sender are more nuanced.

Particularly, we show that the dynamics of an interaction are not trivial: IER goal attainment can explain the immediate well-being consequences for the sender.

Managerial implications

The organizational frontline is transforming and service organizations need to adapt. The rise of AI holds a wealth of opportunities and pitfalls at the same time. Managers need to understand how they can most effectively integrate AI-based technologies for the benefit of their customers (i.e. improving the customer experience) as well as their employees (i.e. improving their well-being) (Larivière *et al.*, 2017; Wirtz *et al.*, 2018). While AI holds many benefits through automating inward-looking processes, particularly in the context of outward-looking interactions with customers, it holds tremendous potential to augment rather than replace human service employees (Wilson and Daugherty, 2018). Service work is largely regarded as resource depleting. Especially the requirement to constantly recognize and regulate own and customers' emotions depicts a major challenge for service employees (e.g. Grandey, 2003). Our results suggest that augmenting employees with an emotion recognition AI bears upward potential for a more effective IER of customers. Service employees benefit by redirecting resources from recognizing emotions to actually managing customer emotions.

As an ancillary effect, more effective IER appears to culminate in increased well-being levels on the employee's side (cf. Niven *et al.*, 2012). AI augmented employees enjoyed higher levels of goal attainment and as a consequence reported more positive emotional states. Thus, managers may not only regard the augmentation of service employees as a contribution to effectiveness, but also as a tool to buffer the undesirable interpersonal consequences of service work on the mental and emotional condition of service employees. The underlying study provides an angle to employ AI as an intervention strategy to counter the resource depleting effects of engaging in IER.

In general, our findings indicate the potential of AI to augment rather than purely substitute humans in the organizational frontline with positive outcomes on employee performance and well-being. However, at the same time the results caution a radical integration of AI on the employee's side. The consequences of any AI-based technology that challenges employee psychological resources may turn out to be a double-edged sword, at least in the early phases of its introduction. Our results show that next to the benefits derived from the particular AI support, service employees likely have to cope with elevated levels of work stress (Ayyagari *et al.*, 2011). It is hence a managerial task to pay attention not to overstrain frontline employees with the AI augmentation. Possibilities to counter these negative effects include a clear delineation of employee (vs technology) roles, targeted training of employees before rolling out the new AI technology and closely monitoring its effect on employee well-being. However, here it is important to consider a potential J-curve effect on well-being and maybe even performance-related outcomes. Related research has identified a novelty effect for users interacting with innovative (AI) technologies, which is expected to last around two months of use (Sung *et al.*, 2009; Wells *et al.*, 2010). Managers should hence allow some time until the AI technology is fully integrated into daily operations, before assessing its implications.

Limitations and future research

Notwithstanding the benefits of conducting a field study, with real service employees and under real working conditions with immediate practical relevance and high external validity, it also bears some drawbacks. Hence, future research might test the results obtained from actual service interactions in a more controlled laboratory environment in a randomized control group experimental design. In our study, employee participants were free to opt out of the study, potentially biasing the results toward more technology-ready employees. In a related vein, data collection during regular business operations restricted us in the scope of items we could assess after each call (however, see Bergkvist and Rossiter, 2007).

Moreover, while employees in the AI extension condition were more successful in attaining the goal of regulating customer emotions, all measures were subjective, and we cannot entirely rule out that, contrary to experimental instructions, service employees have been influenced by the AI in their assessment of a customer's emotion at the beginning and the end of a service interaction. It would be an interesting complementary avenue to our study to employ objective measures for IER activity, goal attainment, perceived stress and affective well-being. Even the reliability of the AI is not entirely objective, as it has been trained by humans who, despite their profession as experts in emotion recognition, are not infallible. Hence, a particularly promising route for future inquiries would be to access the raw conversation data and to triangulate agent data with objective, third-party coding of emotions.

The underlying study provided evidence that successful IER goal attainment may explain the process of how augmenting service employees with an emotion recognition AI boosts affective well-being. Even though this theoretical account is in line with prior work on goal attainment (Harris *et al.*, 2003) and particularly (intrapersonal) emotion regulation (Wong *et al.*, 2017), the study design did not allow to entirely rule out a rivalry explanation. In a customer service context, it is generally expected to regulate customer emotions positively (Grandey, 2003), and hence, service employees in our study mainly attempted to upregulate customer emotions. Thus, goal attainment in our context was highly correlated with a (more) positive emotion feedback from the customer. We submit it to future research to disentangle the underlying process further in a context where people also have motive to engage in negative IER (Niven *et al.*, 2019).

Results indicate immediate effects of augmenting service employees with an emotion recognition AI on affective well-being. While it is striking to observe that even single incidents suffice to produce measurable and significant effects, it remains elusive what the long-term effects are. We expect that the stress related to the introduction of a new AI technology fades away as soon as service employees have become accustomed to collaborating with the AI (Sung *et al.*, 2009; Wells *et al.*, 2010). As a consequence, only the positive effects of successful IER goal attainment should remain, while working with the AI may eventually even lead to a *less* stressful experience. Unfortunately, we were only allocated a restricted period of time for the field study not allowing us to assess these long-term effects. Moreover, it would be interesting to assess potential cumulative effects of a series of (un) successful IER episodes and the effects it has on the long-term acceptance and integration of the AI. Another aspect concerning our stress measure is that it possibly captured stressors unrelated to the introduction of the new technology. Even though we would expect these factors to be balanced across conditions, we cannot entirely rule out that other stressors were dominant in either condition. Future research might disentangle these different stressors.

Finally, the specific service and cultural context of our study is restricted to pension fund customers who are approaching or who have already entered pension age in a Western, well-educated, individualized, relatively rich and democratic country. It is conceivable that customers in a different cultural context or those of a different demographic express emotion differently and react to IER in a different form (see e.g. Grandey *et al.*, 2010). For instance, IER may have an even larger effect in purely complaint-based service hotlines and for more cultures with stronger display rules such as the United States.

Our results suggest that AI can be employed to support the resource integration between service providers and customers (Kaartemo and Helkkula, 2018). Thus, we show how AI can be an enabler of resource integration, creating value for customers and employees in a new hybrid system, where the service encounter is in-between a person-to-person and a person-to-information system (Glushko and Nomorosa, 2013). Rather than humanizing a technology (Fan *et al.*, 2016), we demonstrate the potential benefits of extending humans with AI technology. Reflecting our study against extant conceptual research on the role of technology in the future of service interactions (Van Doorn *et al.*, 2017), we note that social presence can differ between the customer's and the employee's perspective. While our study context is a classic example of a high human social presence/low automated social presence service encounter from the customer's perspective, it is a high human social presence/high automated social presence service encounter from the employee's perspective. We would like to encourage future research to explore such hybrid systems in more detail and include the employee's experience in extended conceptualizations of the service encounter.

In the long-term, digital agents (examples include Amazon's Alexa, Microsoft's Cortana, Apple's Siri and Google's assistant), whether embodied or virtual, may even play a more prominent role in the frontline, directly advising and interacting with consumers in the marketplace (Dawar and Bendle, 2018). It will be interesting to see how AI will continue to shape the organizational frontline, whether in the future both employees and customers will be augmented with AI-based technology to optimize their interactions and what effect this will have on the social interactions in the marketplace.

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