Affective Displays in Service Interactions

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List of Publications

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* My role in the publications listed above was hypotheses and theory development, data wrangling, statistical analysis, and writing.

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ABSTRACT

Affective displays (i.e., displays of emotions, moods, and attitudes) imbue customer-service interactions, where employees have something the customer wants or needs, and customers are integral to employees' job performance. Yet previous research relied on one-time or aggregated measures of affective displays, neglecting the nuances of display dynamics. We fill in this gap by analyzing text-based (chat) service interactions at the level of individual messages to unravel the effects of customer and employee affective displays within the interaction.

The digital data and newly developed tools for sentiment analysis that we use allow exploration of affective displays in large samples of genuine customer service interactions. Thus, the research provides objective, unobtrusive views of customer and employee affective displays that draw directly from their expressions, with no self-report intervention and biases.

In the first paper, we demonstrate insights that can be gained from analyzing archived resources to extract data based in genuine service interactions between service employees and customers. For example, examining whether customer affective displays vary with the time of day or day of the week a service interaction occurs, or looking at the evolution of affect customers display within an interaction.

In the second paper, we analyze employees' emotional labor less recognized requirement to attend to the customers' affective displays. We theorize that employees are influenced by their partner affective displays (i.e., acting in response-dependence) more than customers and support this theory in two studies. In Study 1, we examined field data comprising 1,320,392 customer and employee messages from 164,899 real-life chat-based service interactions and used automated sentiment analysis to identify displays of positive and negative affect. In Study 2, we

used simulated service interactions to examine discrete emotions. Using different methodologies, both Study 1 and 2 found that employees and customers differ in their response-independence and response-dependence affective behaviors. Study 2 also demonstrated that employee response-dependent affective behavior improves customer outcomes.

In the third paper, we zoom out into full service interactions. We suggest that customers rely on affective cues when retrospectively reporting on their satisfaction with service interactions. Our analyses confirm the effects of overall, peak (most extreme) and end (final) affective displays of customers and employees on customer reported satisfaction. We further confirm that the contribution of affective displays to explaining customer reports of satisfaction is much greater than the contribution of objective, operational measures such as employee response time or issue complexity. We additionally hypothesize and confirm that these effects are more pronounced under uncertainty, which we argue occurs following an outcome service failure. We confirm our hypotheses with 23,645 real-life service interactions, comprising over 277,000 messages of customers and employees.

Our data provide a unique lens into the dynamics of affective displays in service; results that are not obtainable using traditional research methods. Our findings focus attention on the need to analyze mutual affective displays, and on specific aspects of service interactions to improve understanding of the outcomes of an interaction.

LIST OF ABBREVIATIONS AND NOTATIONS

APIM	Actor-Partner Interdependence Model
B	Non-standardized regression coefficient
β	Standardized regression coefficient
CSAT	Customer satisfaction
Cust	Customer
DF	Degrees of freedom
Emp	Employee
F	F distribution
F(v1, v2)	F with v_1 and v_2 degrees of freedom
M	Sample mean
N	Total number of cases
n	Number of cases (in a subsample)
R^2	Multiple correlation squared
RT	Response time
SD	Standard deviation
SE	Standard error
Time T	Time of a focal message
VIF	Variance inflation factor
Δ	Increment of change

INTRODUCTION

Can anyone live and work in the twenty-first century without digital service interactions? We buy through Amazon or Ali Express, book flights and hotels through Expedia or Booking, and communicate with service agents through chats, texts, Facebook, Twitter, and email. Affect in service is equally ubiquitous – it is rare to talk about service without having someone intervene to recount a frustrating or annoying service situation.

The prevalence of service in modern life has been accompanied by increasing research attention to affect in service. Available research of affect in service has relied primarily on self-report data (e.g., Grandey et al., 2004; Groth & Grandey, 2012), qualitative explorations or field work based on observations (e.g., Pugh, 2001), and experimental manipulations (e.g., Goldberg & Grandey, 2007; Rafaeli et al., 2012). Now digital age twenty-first-century technologies afford new sources of data, and new approaches to data collection and analyses, and provide fascinating opportunities for new insights.

For a long time, service has been conducted through telephone call centers, where "calls are recorded for quality assurance" (and perhaps for legal reasons). Such recordings offered invaluable access to actual communication between service employees and customers. However, utilizing this resource traditionally relied on the labor-intensive process of transcribing the interactions and manually coding key themes (e.g., Rafaeli et al., 2008).

Increasingly, modern-day technologies afford tools for automatic recording and retrieval of the full data comprising service interactions. Additionally, traditional service media (face-to-face, telephone) are increasingly being replaced with sophisticated technology-mediated encounters. One such development is services delivered through written messages (chats, texting, twitter.) Communication can be through corporate websites, Twitter or Facebook, or through mediators, such as http://LivePerson.com, a company that sells other firms tools for text-based service communication between customers and service employees.

From a research perspective, these digital age technologies provide a gold mine of archives of service interactions and unique opportunities to promote our understanding of affect in service delivery. Digital age service delivery also provides the opportunity to access direct measures of meta-data about service interactions. Not only is the full content of the service interactions accessible, but it can also be matched with when the interaction occurs, how long it lasted, what else happened before or after the interaction, and more.

Affective Displays in Service

Expressions of emotion imbue interpersonal interactions and influence observers (Hareli & Rafaeli, 2008; van Kleef, 2009) by evoking emotions, attitudes, and behaviors (Frijda & Mesquita, 1994; Hareli & Rafaeli, 2008; Keltner & Haidt, 1999). Observers infer how others view a situation from their emotional expressions, and are subsequently influenced by these interpretations (van Kleef, 2009; van Kleef et al., 2011). Additionally, individuals use their own emotional expressions to influence others (van Kleef et al., 2011). Expressions of emotion are particularly salient in customer service interactions (Groth et al., 2019), in which employees possess something of value to customers (Lawler, 2001) and customers' feelings and behaviors are integral to employees' job performance (Mills & Morris, 1986).

Throughout this work, we use a broad, global-type concept of "affective displays" (e.g., Dallimore et al., 2007; Staw et al., 2019), which refers to displays of affective phenomena such as emotions, moods, and attitudes (Bagozzi et al., 1999; Scherer, 2005). Importantly, following Ashforth and Humphrey (1993), we focus on affective *displays* (Dallimore et al., 2007; Scherer, 2005; Staw et al., 2019; Trougakos et al., 2008; Wang et al., 2017), not on felt affect, because we theorize on interaction dynamics, where displays can be observed and are likely what influence partners.

Our theory relies on a view of service interactions as a series of events. We construe service interactions as composites of individual messages that can convey what a person feels or thinks, or what they choose to display—these may be distinct, especially for employees acting out display rules, though the partner to the interaction (the customer) may not necessarily be aware of this. Specifically, we focus on text-based service interactions, where customers express their issues and affect in writing. In this context, vocal feedback or facial nonverbal displays (e.g., Dallimore et al., 2007) are not available but the texts of both customers and employees can be analyzed. Customers display their affect—to the extent that they do—in their messages. Employees provide solutions and information to customers, and express suitable affect according to the organizational requirements, also in writing. Customer and employee displays of affect are accessible to their interaction partners the moment they appear on the screen.

Service as a Sequence of Messages and Affective Displays

Service interactions comprise a sequence of messages that unfold over time (Verhoef et al., 2004). Customer evaluations of these messages – i.e., of the complete service episode – are collected by service managers and utilized as indicators of service quality (Andreassen, 1999). Affective displays of individuals in this sequence can vary between messages, reflecting what Weiss and Cropanzano (1996) call "affective events." An affective display in a message may or may not reflect precisely what a person feels, but it is still integral to the interaction, and thus, we propose that it can serve as a useful indicator of customer satisfaction.

Customer affective displays might be negative; for example, customers may display anger ("I'm really angry about the commission!", Glikson et al., 2019; Jerger & Wirtz, 2017;

"Your service is extremely inefficient! ... This is an outrage!", Miron-Spektor et al., 2011), incivility ("I hope you're at least somewhat competent", Frey-Cordes et al., 2020; "Can't you count? One", Henkel et al., 2017), or aggression ("For such an easy job you'd think you could get through these line-ups a lot faster! No wonder this is the best job you could get", Hershcovis & Bhatnagar, 2017). Customer displays can also be positive, showcasing displays of gratitude ("You were very helpful. Thanks!", Biron & Bamberger, 2010; Bock et al., 2016), or politeness ("Oh, I totally love your uniform … I'm sure you're able to help me", Frey-Cordes et al., 2020).

Research indicates that during service failure and recovery, affective displays of customers reflect the emotions experienced, albeit perhaps not fully or perfectly. Smith and Bolton (2002) reported that expressions of discontent prevail in customer responses to service failures (e.g., "discouraged", "distressed"). Schoefer and Diamantopoulos (2008a), who developed a scale of emotions during service recovery (ESRE), reported that some emotions, such as discontent (assessed by the items: "upset", "angry", "sad", "in a bad mood", and "annoyed") are highly frequent, whereas others, such as pleasure (assessed by the items: "joyful", "happy", "proud", "warm feelings", and "being valued") and involvement ("attentive", "active", and "interested") are also present, but with less frequency.

At the other end, employee messages may include apologies and empathetic responses (Herzig et al., 2016); for example, "I'm sorry. They are being unpacked at the back" (Zhang, 2010) or "I am really sorry; of course, I will fix you another one right away" (Henkel et al., 2017). Employee messages can also be positive, conveying happiness ("I am happy to offer you this movie", Cheshin et al., 2018), cheerfulness, or gratitude (Herzig et al., 2016). Employee and customer messages can also be purely technical, and include no affective display ("My name is …, and my cell phone number is ...", "We can replace the phone for you... Will someone be home at these times to meet the delivery man?", Rafaeli et al. 2012). Since affective displays are relatively accessible to organizations, we propose that they should be considered a valuable source of information.

The Current Research

We contribute to the theoretical understanding of affective displays in interpersonal processes at work by examining interdependent customer and employee affective displays during service interactions. This work, therefore, examines the third level of Ashkanasy's (2003) model of emotions in organizations: the interactional level. We concur with Waldron (2000) that this level is key to understanding emotions in organizations, as they are social systems dependent on social interactions to accomplish goals.

We aim to expand the scope of research on affect in service delivery. In the first paper of this work, we obtain descriptive insights about affective dynamics in service interactions, afforded by analyses of archives of digital service interactions and using objective, unobtrusive measurements. Such interactions are common in the current service ecosystem, and there is seldom any prior history between the customer and the employee. The affect that customers and employees display in this type of interaction is yet to be thoroughly studied (Rafaeli et al., 2020).

In the second paper, we take a dyadic approach, which more fully explores both intrapersonal and interpersonal dynamics of affective displays (Tse & Ashkanasy, 2015). We show that rather than consistently displaying positive affect, as might be implied from the famous "service with a smile" requirement, employees monitor the affective displays of customers and adjust their affective responses. Also, we show that this adjustment of employees improves customer displayed affect and evaluation of the employee performance. Lastly, in the third paper, we suggest that customer and employee affective displays throughout a service interaction are useful indicators of customer post-service evaluations of their satisfaction. More specifically, we suggest that specific displays are important, and that they are especially useful following an outcome service failure, where customer issues were not resolved.

PAPER 1: INSIGHTS FROM ANALYZING DIGITAL TRACES OF SERVICE DATA

In the first paper of this work, we analyzed organic digital traces data of service interactions conducted through written chats. We obtained the data from a firm that maintains platforms for text-based interactions between customers and brands. LivePerson (http://LivePerson.com) serves over 18,000 business customers, who communicate with their customers through chat. The LivePerson platforms facilitate 25 million service interactions a month, accumulating archives of organic data.

Our research used a sentiment analysis tool to obtain unobtrusive insights about displayed affect in service interactions. Sentiment analysis tools can be used to automatically analyze large samples of customer service interactions with different types of research foci (Rafaeli et al., 2019). As elaborated next these analyses are unique in three ways: (1) they rely on analyses of large samples of actual expressions of customers and employees, suggesting high external validity; (2) they are done automatically, with no human intervention, so offer high reliability, and minimal biases due to human error; (3) they provide access to new variables and analyses that previous research on affect in customer service could not access without a major investment of time and effort; they also provide data on different time periods, service employees, and customers, allowing for comparisons and insights at a higher level of granularity than most previous research.

A large magnitude of data is the first benefit of the research we promote in this work. For example, the analyses described below are based on data retrieved from an archive comprising 216,814 service interactions (or some 2 million text messages). Moreover, the data represents multiple service employees and customers who conversed at different times. These samples overshadow typical data sets used in prevailing research on affect in customer service, where samples are often a few thousand at best. The data are large enough to provide insights that are highly likely to be representative of the population, and any findings with such data likely have external validity. Importantly, additional samples of data can be retrieved easily for comparison or to replicate as a test of the robustness of any given finding.

The organic nature of the data frees researchers from the reliance on service employee or customer self-reports. Organic data document people's spontaneous behavior, with no intervention and potential bias due to researchers' predictions or planned research design. The digital data and newly developed tools for sentiment analyses allow exploration of affect in large samples of genuine customer service interactions. This genuine data and methods that we use offer substantial benefits: the research provides objective, unobtrusive views of customer and employee affective displays that draw directly from their expressions, with no self-report intervention and biases (Donaldson & Grant-Vallone, 2002; Paulhus & Vazire, 2007; Webb et al., 1966; Xu et al., 2019). This work thus provides a lens into the dynamics of affect in service that could not be obtained using traditional research methods. For example, we report data that offer insights into the affect customers actually display to service agents, as opposed to the customer affective displays that employees remember or recall, which is what self-report data represent.

The data also include a lot more granularity than most other research on affect in customer service. Data also span wide ranges of time and resolutions from minutes and days to months. The breadth of the data allows us to unravel some issues regarding affective displays in customer service, including issues that previous research constraints prohibited. For example, we report data on affect displayed at different times of day, or different days of the week. Also, the data allow exploration of the evolution of affect and its effects over time. To illustrate, we report below on patterns of customer and employee displays of affect over the course of interactions, or during the shift of a specific service employee.

Of course, our data show dynamics of affective displays in chat service interactions which have a different nature than phone or face-to-face interactions. But these data nonetheless provide informative insights into the genuine dynamics of service interactions. Also, to retain the privacy and anonymity, we do not know anything about the employees or the customers and cannot report demographic information. The data does include, however, an ID code identifying (and keeping anonymous) the employee and customer in each interaction. This means we can track multiple messages of the same customer or employee. As described below, we can therefore trace the pattern of affect customers and employees display over the course of interactions, or the full load of customer affective displays an employee experiences over the course of a shift.

1.1. SentiStrength: A Sentiment Analysis Tool

We assessed the affective displays in each customer or employee message using an automated sentiment analysis tool called SentiStrength (http://sentistrength.wlv.ac.uk/), which is uniquely valid for analyzing affect in individual messages, as other tools are designed for analyses of longer, narrated texts (e.g., Yom-Tov et al., 2018). It searches through each message to identify words and word stems that appear in widely-used dictionaries of sentiment words (e.g., Linguistic Inquiry and Word Count; Pennebaker et al., 2001) and assigns each word both a negative score that can range from "not negative" (-1) to "extremely negative" (-5), and a positive score that can range from "not positive" (+1) to "extremely positive" (+5). Scores are then modified based on various predefined rules; for example, capital letters strengthen the score, whereas negation words (e.g., “not”) neutralize the score. These scores are then combined into a single bipolar sentiment score, such that each message receives an overall score ranging from “extremely negative” (-4) to “extremely positive” (+4) (see Thelwall, 2017). This final score is the one that we used in our analyses.

We saw this single bipolar score as useful for our analyses. Each message is described with a single positive/negative value, with a zero point which is neither positive nor negative, similar to previous research that relied on a continuous measure of emotion (Fredrickson & Kahneman, 1993; Gabriel & Diefendorff, 2015; Verhoef et al., 2004). We see this bipolar score as designating the intensity of the positive or negative affective display in the message. A negative score denotes a message that overall expresses negative affect, and a positive score denotes an overall expression of positive affect. For example, the message “I am very sorry to hear that you’re unsatisfied” receives a negative score of -2, and “You’re most welcome - glad to assist!” receives a positive score of +2. Some examples and demonstrations of the tool can be found in its website (http://sentistrength.wlv.ac.uk/).

These data are based on the assumption that each individual message either does not include any affect or conveys one dominant affective display that is either negative or positive. To support this assumption (and our use of the bipolar scale), we used crowdsourcing to recruit participants to read a sub-batch of 1764 messages and indicate if the message reflected a negative or positive emotion, both, or neither. Because of privacy concerns, we could not use the authentic sentences in this crowdsourcing task; therefore, we used sentences from simulated text-based service interactions that were collected for another study. The tagging showed that only one of the 1764 messages (0.00056) included both positive and negative emotions, clearly a negligible proportion. Similar results were reported by Yom-Tov et al. (2018). Moreover, similar to Baier et al. (2020), we ran correlations between the separate positive and negative scores and the bipolar score and found high Pearson correlations of .697 (positive) and .745 (negative), which further reinforces our use of one bipolar scale.

1.2. Insights

The unique data we described above attempt to address a large range of questions. Our goal in this paper is to illustrate some of the insights that such data can provide about issues and aspects of affect in customer service that have not been previously explored. In this paper, we do not report on hypothesis testing, but rather an overview of descriptive insights about the phenomenon that is the focus of this work – affective displays in service delivery.

In Figure 1 we show an analysis that focuses on affect that customers display at the beginning and the end of service interactions. Figure 1 shows that the affect customers display varies (and improves) from the first to the last message. In aggregate, customers appear to start off interactions with mostly neutral affect (affective scores around 0.1), and end interactions with expressions of mildly positive affect (affective scores around 0.7). This pattern is not related to time of the day an interaction occurs.

A more refined look at the affect customers display within interactions is depicted in Figure 2, which shows the affective displays typical to multiple stages or sections within interactions. This type of analysis portrays service interactions as a sequence of affective displays. Since service interactions vary in the number of messages they comprise, we must first create a standardized metric that allows comparisons of interactions with different length. We obtain such standardization by splitting all interactions into 10 roughly equal sections; this standardization means that sections in different interactions may comprise a different number of messages, but all interactions comprise exactly 10 sections (or 10 deciles). Using such standardization, we were able to average the affective scores of all customer (or employee) messages in each section and obtain a metric of customer affect per section. Each interaction is thus defined as comprising 10 sections, and 10 affective scores. The result of this standardization allows us to depict the flow of affective displays over the course of multiple interactions, as shown in Figure 2.

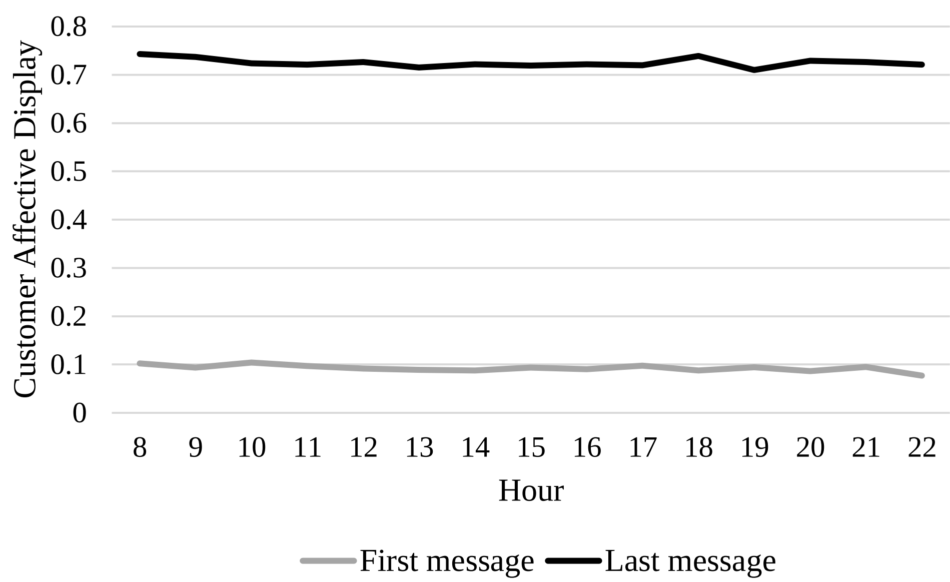

Figure 1.
Customer affective display in first message and last message of an interaction with a service employee (N = 216,814 interactions)

Figure 2 suggests that interactions have a standard structure comprising three within interaction stages – opening, middle (or main), and closing. Similar to Figure 1, Figure 2 again suggests that interactions open with mostly neutral customer affective displays, and end with more positive customer affective displays. The main and middle of interactions shows customers as being mildly positive. Figure 3 shows negligible variations between replications of the analysis of affective displays by section at different hours, and on different days of the week.

It is not surprising that customers express more neutral affect at the starts of their interactions, since, in some cases, initiating a service interaction means the customer has an issue that needed to be resolved. The more positive affect expressed toward the end of interactions presumably suggests that the interaction helped resolve the customer's issue. The middle sections, where there seems to be little expression of affect by customers, likely focus on the technical issues relevant to the customer issue or its solution. Figure 2 also suggests that employee displays, in contrast to customer displays, start with positive affect, presumably because the employee greets the customer. Then, employees continue with more neutral expressions, and end with positive affect toward the end of the interaction, similar to customer expressions.

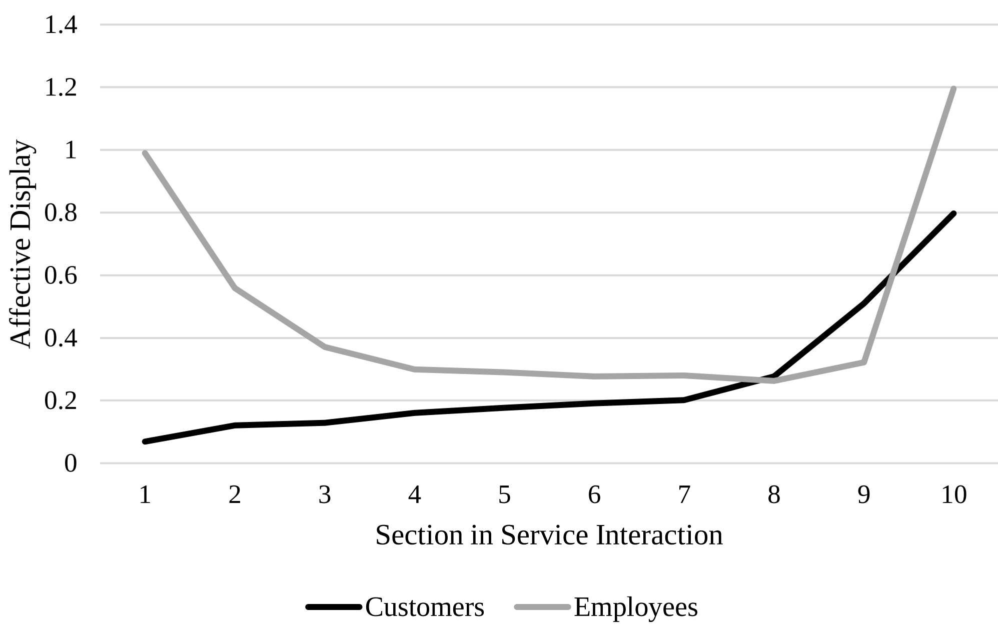

Figure 2.
Aggregated affective displays of customers and employees in different sections of service interactions (N = 216,814 interactions)

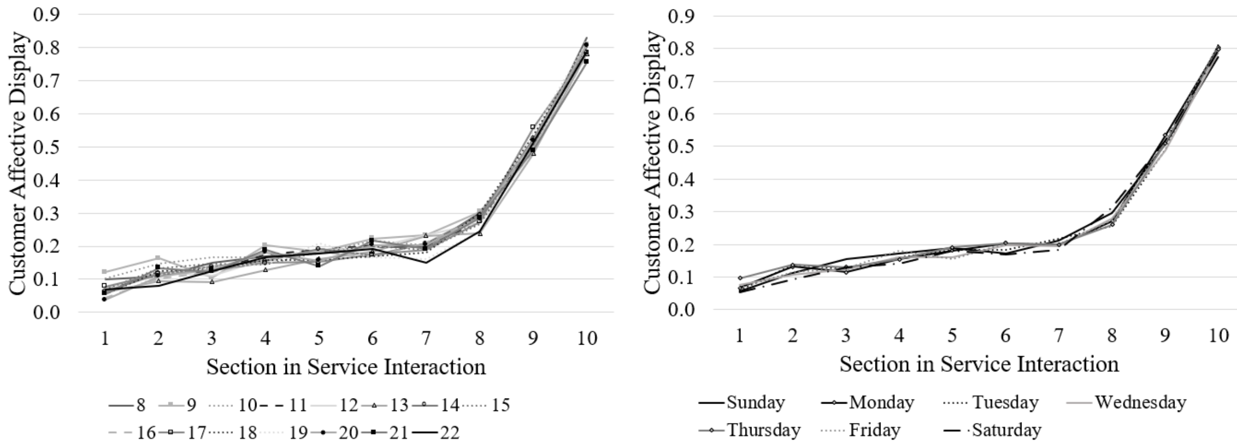

Figure 3.
Aggregated affective displays of customers in different sections of service interactions, at different hours of the day and different days of week (N = 216,814 interactions)

An additional perspective that research relying on digital traces data can provide is the relationship of affective displays during service interactions to customer evaluations of the service employee and service interaction after the service ended. For this perspective we integrate the analyses of affective displays with data we have regarding customer evaluations of service. The firm we work with, like many service providers, follows up on service interactions with a text message asking customers to respond to a short survey assessing their satisfaction with the service they received. The survey asks basic questions, such as "*How satisfied were you with the service from our advisor?*" allowing responses of 1 through 5, with 1 indicating high dissatisfaction, and 5 indicating high satisfaction. Responses to such post-service surveys are voluntary and hence will always only represent partial data for all the customers in our samples. Notwithstanding, the sample sizes of our analyses here are still substantially larger than most sample sizes in previous affect-in-customer-service research.

Figure 4 depicts the pattern of affect displayed by customers within their service interactions, broken down by the customers' response regarding their level of satisfaction with the performance of the service employee. Figure 5 depicts a similar analysis with the affect displayed by employees. The frame of reference in Figure 4 – the bold line – depicts the mean affective display throughout the interaction in the population of customers who did not respond to a post-service survey. Figure 4 shows that the affect displayed by customers who were extremely satisfied with the employee performance (rating of 5) climbed higher, to include displays of more positive affect. In contrast, affect displayed by customers who were dissatisfied with their employee's performance (rating of 1) remained low throughout the interaction. The figure also shows that these customers started out with nearly the same level of affect as most other customers, negating the possibility that these customers started out with more negative affect.

Figure 5 also shows the patterns of employee displays. The figure suggests that displays at the beginning of the interactions are quite positive and do not seem to differ between customers who were satisfied and customers not satisfied after the end of the interaction. But employee displays at the end of the interactions seem less positive for customers who were dissatisfied, implying co-variation of employee affective displays at the end of an interaction and customer satisfaction. Overall, Figure 4 and Figure 5 suggest that customer and employee affective display scores throughout interactions are higher with higher post-service customer satisfaction.

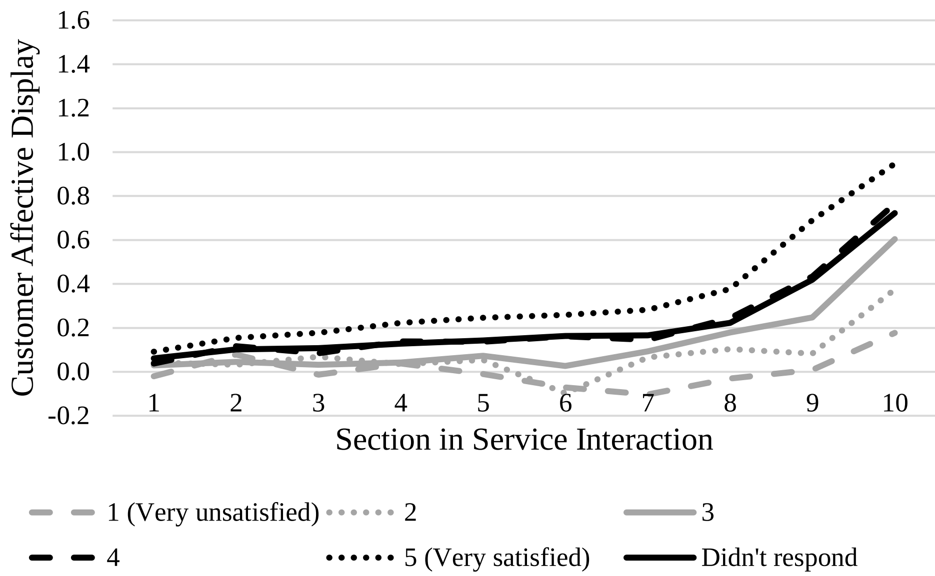

Figure 4.
Aggregated affective displays of customers across ten deciles of interactions, by customer satisfaction levels

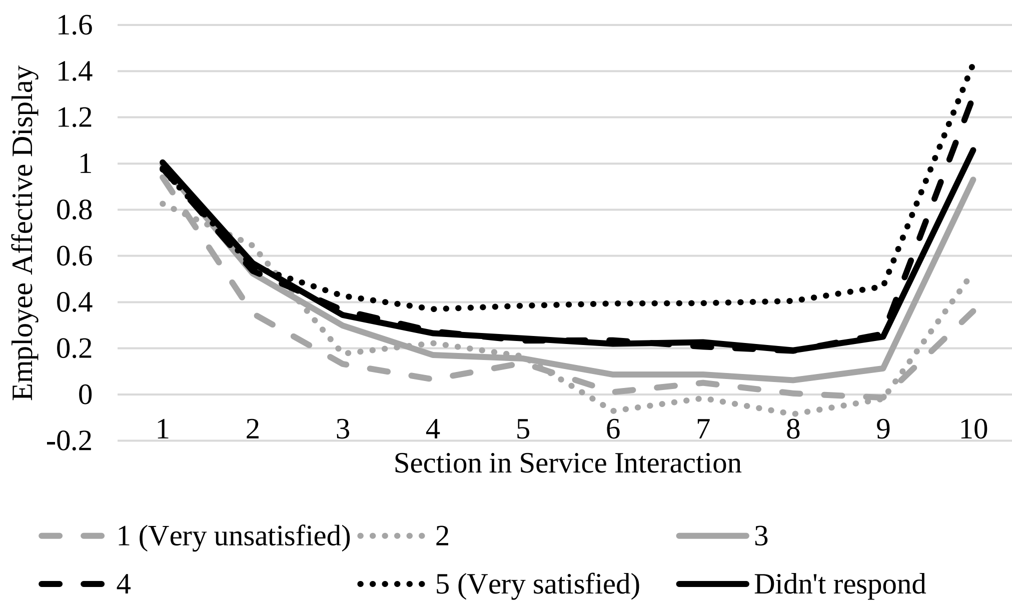

Figure 5.
Aggregated affective displays of employees across ten deciles of interactions, by customer satisfaction levels

Service employees often report encountering a lot of hostile customers (Grandey et al., 2004). Our data allow addressing this question in two ways. First, as depicted in Figure 6, we tracked the sum of customer positive and negative affective displays (resulting from 102 interactions) encountered by a random employee on a random workday. We observe that over a relatively short time, the employee encounters multiple affective displays of multiple customers. The result, we propose, is an emotional rollercoaster for this employee. But, looking at the affect encountered by that one employee carries the risk of a sampling bias. Perhaps we randomly selected a particularly problematic employee? Thus, we also compute an aggregation of affect that all customers convey over the course of a full workday across all employees. This depiction removes the concern of a sampling error, an outlier, or special case employee. Figure 7 thus shows the number of positive and negative affective displays expressed by all customers over the course of a full workday. The picture depicted by Figure 7 shows a rise and fall of displays of positive and negative affect. These transitions in customer affective displays evident in Figure 6 and Figure 7 are probably the most difficult part of service employees' work, similar to the depleting and debilitating social influence that Rafaeli and Sutton (1991) described in encounters with emotionally contrasting social expressions by interaction partners.

These analyses only scratch the surface of the types of insights that future research can suggest utilizing the opportunities that we highlight. In the second paper of this work, we further connect customer affective displays to subsequent employee affective displays. In the third paper of this work, we connect customer and employee affective displays within service interactions to customer evaluations of satisfaction after the interaction.

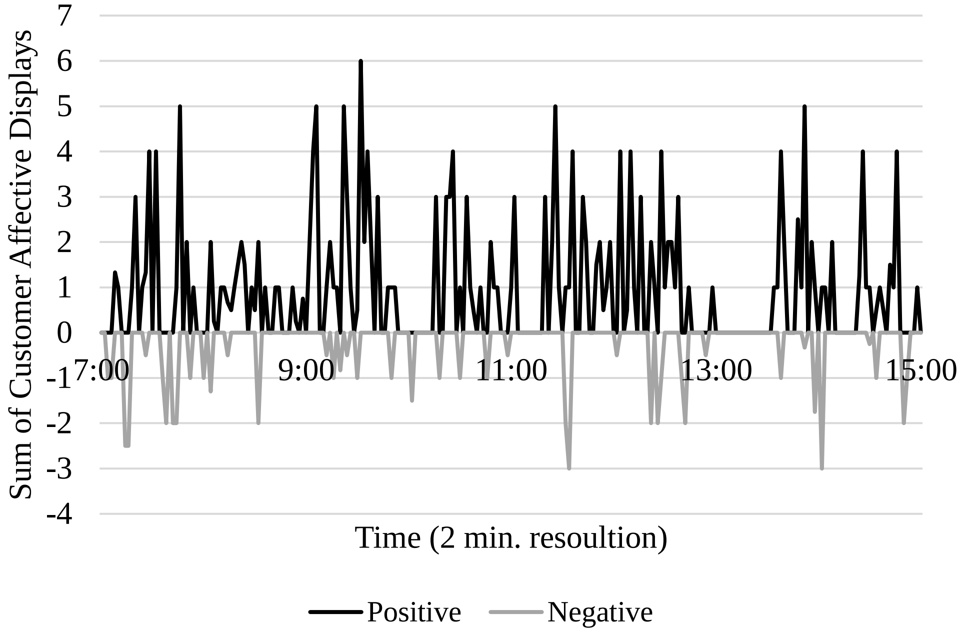

Figure 6.
Sum of customer affective displays encountered by one employee during a workday (N = 102 interactions, n = 447 messages)

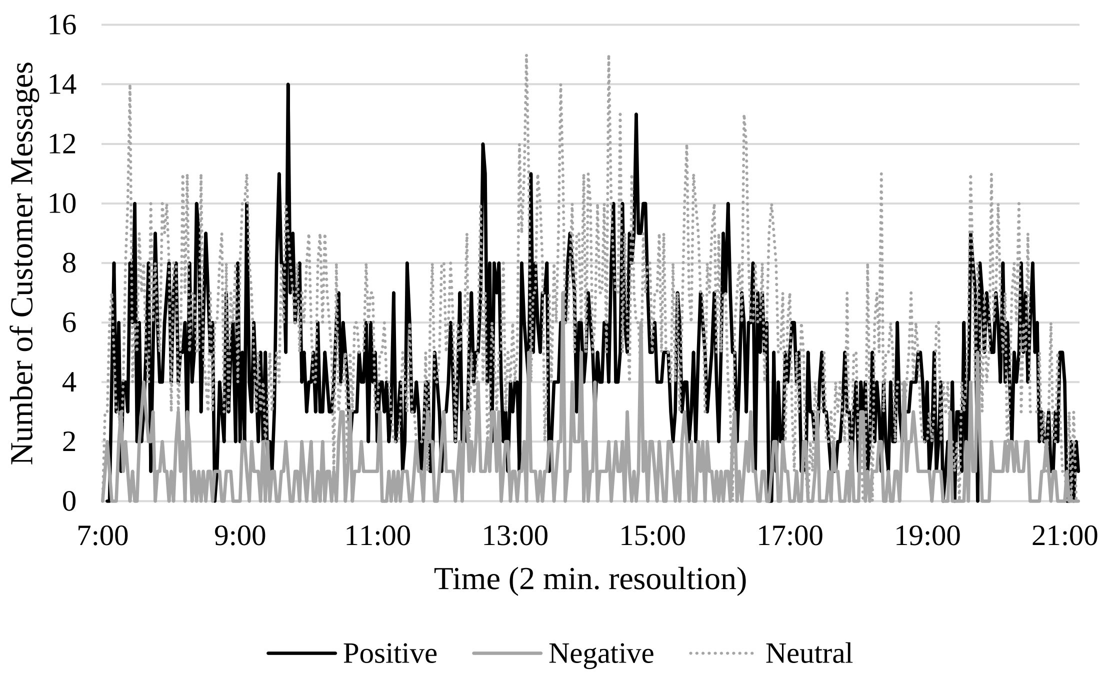

Figure 7.
Number of customer affective displays encountered by all employees over the course of a workday (N = 958 interactions, n = 4,739 messages)

PAPER 2: EMOTION REGULATION IN SERVICE INTERACTIONS: RESPONSE-INDEPENDENCE AND DEPENDENCE IN EMOTIONAL LABOR

2.1. Introduction

This paper builds on Rafaeli and Sutton's (1987, 1989) suggestion that feedback from customers influences employees' expressed emotions, leading the employee to maintain, alter the intensity of, or change their expressed emotion. Feedback loops are also likely, wherein customers' affective displays influence employees' affective displays, which in turn influence subsequent customer affective displays. These affect feedback loops make salient the emotional requirements of service jobs and the need for service employees to regulate their displayed affect (Diefendorff & Gosserand, 2003). Our theoretical analysis suggests that emotional labor places employees in a predicament of competing requirements. Employees are expected to provide "service with a smile," which implies recurring displays of positive affect. At the same time, employees are in a lower power position than customers (Rafaeli, 1989) and are expected to be attentive and to adapt their affective displays to customers. In occupying the higher power position, customers are not faced with this predicament; rather, they are motivated to fulfill their own needs, and thus can strategically use affective displays to signal their needs to employees. In this paper we utilize a dyadic approach, which enables us to more fully explore both intrapersonal and interpersonal dynamics of affective displays (Tse & Ashkanasy, 2015).

2.1.1. Interpersonal Emotion Regulation in Customer Service

Conceptualizing emotional labor in service work as interpersonal emotion regulation at work expands upon the idea of emotional labor. This conceptualization suggests that employees not only regulate their own affect, but also attempt to regulate others affect, namely their customers', creating dual regulation which increases the complexity of their emotional labor. Theoretical foundations for interpersonal emotion regulation at work were posed by Troth, Lawrence, Jordan, and Ashkanasy (2018); our study broadens and tests some of their ideas. The interpersonal emotion regulation framework proposed by Zaki and Williams (2013) helps to understand the aforementioned complexity. Zaki and Williams (2013) identified two emotion regulation patterns: within-person, intrinsic regulation (i.e., people regulating their own emotions) and between-person, extrinsic regulation (i.e., people attempting to change others' emotions). They further suggested two types of processes that support interpersonal regulation: (a) response-independent processes, which do not rely on a partner's feedback, and (b) response-dependent processes, which do rely on a partner's feedback.

In the context of customer service interactions, service employees must simultaneously engage in multiple regulation processes at work, navigating co-occurring intrinsic and extrinsic emotion regulation processes (Troth et al., 2018, p. 533). Emotional labor research has previously implicitly referred to intrinsic emotion regulation, suggesting that employees attempt to change their own emotions, through deep or surface acting (Grandey, 2003). Yet, at times, emotional labor refers to employees' influence on customer outcomes (e.g., satisfaction, purchase, word-of-mouth; Liu et al., 2019; Pugh, 2001). In an attempt to achieve these outcomes, service employees are tasked with the responsibility of exercising extrinsic interpersonal emotion regulation to influence customers to feel more positively (e.g., Niven et al., 2009). In the current paper, we focus only on extrinsic interpersonal emotion regulation. We examine affect that employees (and customers) express (in writing).

As part of their efforts to influence customer outcomes, employees must display positive affect, or "service with a smile." In an empirical test of this central element of emotional labor, Sutton and Rafaeli (1988) and Rafaeli and Sutton (1990) coded the extent to which employees smiled, greeted, thanked and made eye contact with customers. Importantly, these analyses did not consider the extent to which employees attended to customers' behaviors or expressions. From the perspective of interpersonal emotion regulation, the consistent display of positive affect by employees suggests response-independence, such that it disregards the behavior of one's interaction partner. However, a limited number of emotional labor studies have referred to employees' attendance to customer needs, affect and/or behaviors. For example, Varca (2007) referred to displays of empathy toward frustrated and angry customers as employee emotional labor. Similarly, Brotheridge and Grandey (2002) used an emotional labor measure, originally described by Best, Downey, and Jones (1997), to ask employees whether they "reassure people who are distressed or upset" and whether they "expressed feelings of sympathy." From Zaki and Williams' (2013) perspective, these studies of emotional labor consider customer expressions, suggesting that employees additionally engage in response-dependent emotion regulation.

On the other hand, customers are exempt from the emotion regulation complexities experienced by employees (Hochschild, 1983). The service encounter, therefore, is characterized by an inherent imbalance in the emotional regulation demands placed on employees and customers. Customers, unlike employees, have the privilege of being self-focused, such that they can concentrate only on regulating their own emotions, i.e., intrinsic interpersonal regulation. They can rely on response-dependent intrinsic regulation, for example by using supportive displays of service employees as a source of comfort (Zaki & Williams, 2013). However, customers can also regulate their emotions independent of service employees (e.g., Grandey et al., 2010), i.e., response-independent regulation (Zaki & Williams, 2013).

The nature of service delivery further complicates service employees' emotion regulation demands. Service occurs in real-time interactions, referred to in service management theory as "Moments of Truth" (Groth et al., 2019). There are actually a series of Moments of Truth, each comprising employee actions and affective expressions. Yet, available scholarly work offers very limited empirical tests, which considered only a few points in service interactions (e.g., before, during and after an interaction; Liu et al., 2019; Pugh, 2001). Importantly, researchers repeatedly call for studies of moment-by-moment shifts in affective displays (Filipowicz et al., 2011; Liu et al., 2019; Sinaceur et al., 2013; van Kleef & Côté, 2018) and available theory supports the presence of momentary effects in customer-employee interactions (Grandey & Gabriel, 2015; Groth & Grandey, 2012); yet, previous research largely reports on single or aggregated measures, and thus are unable to unravel the feedback effects that result from imbalanced emotion regulation.

Our goal in the current paper is to untangle the concurrent flow of affective displays between partners *within the same service interaction.* We do this by analyzing text-based (chat) service interactions at the level of individual messages. This micro-focus allows us to track the affective displays of customers and employees within the interaction. We distinguish between an intrapersonal pattern, in which a person displays a recurring (similar) affect in the course of an interaction (i.e., *response-independent*), and an interpersonal pattern, in which a person displays affect following a partner's displays (i.e., *response-dependent*).

Our research makes several important contributions. First, we conceptualize bidirectional, complementary, and concurrent relationships between affective displays of two partners in the same dyadic interaction at the message level. We use Zaki and Williams' (2013) framework of interpersonal emotion regulation to study service interactions as a dyadic exchange in which different partners use different regulation processes. We respond to Troth et al.'s (2018) call to contextualize theory about interpersonal emotion regulation, by connecting emotional regulation processes to power differences. We identify asymmetry in power as a cause of asymmetry in expectations and requirements, which leads to different affective regulation processes. We propose and document that low power people (employees in our data) are more likely to adjust their affective displays than high power people (customers in our data).

Second, we highlight more complex requirements of emotional labor than previously proposed. We illustrate that employees navigate this complexity by adjusting their own displays to customer displays. We show that customers – who are partners to the same interaction, but not constrained by emotional labor – do not adjust their displayed affect. Third, we connect response-dependence in affective displays to outcomes of dyadic interactions. We show that employee adjustment of their affective displays according to the displays of customers improves customer outcomes.

2.1.2. Emotional Labor and Employee Emotional Requirements

Emotional labor describes organizational requirements regarding emotions that employees should display when interacting with others (Geddes & Callister, 2007; Grandey, 2000; Rafaeli & Sutton, 1987; Sutton & Rafaeli, 1988). In the customer service context, emotional labor is intended to encourage employees to display emotions like cheerfulness, and other "appropriate" emotions (Geddes & Callister, 2007; Grandey, 2000).

A key requirement of emotional labor is employees' *display* of positive affect when interacting with customers (C. M. Berry et al., 2012; Brotheridge & Grandey, 2002; Schaubroeck & Jones, 2000). Specifically, service employees (and their supervisors) report requirements to amplify displays of happiness and neutralize anger (Diefendorff et al., 2006;

Diefendorff & Greguras, 2009; Jones & Rittman, 2002). The goal of managing employees' affective displays is to influence customers (Pugh, 2001; Zapf, 2002), presumably through contagion (Hatfield et al., 1994; Pugh, 2001) or appeasement, thus making customers susceptible to company influence (Gibson & Schroeder, 2002). Research provides evidence for such effects. Tan, Foo, and Kwek (2004), for example, reported that employees' displays of positive emotion positively related to customers' satisfaction with service providers. Tsai (2001) and Tsai and Huang (2002) reported that positive affective delivery by retail sales clerks increased customer willingness to return to a store and recommend it. Employees' adherence to the emotional labor rule of "service with a smile" suggests that employees engage in what Zaki and Williams (2013) regard as response-independent emotion regulation, such that their positive displays do not depend on the customer's feedback.

Hypothesis 1. *Affective displays of service employees include recurring displays of previous affective displays (i.e., employee response-independent regulation).*

In addition to displaying positive affect, service employees are also expected to monitor the extent to which their customers are satisfied (Szymanski & Henard, 2001). To foster customer satisfaction, employees cannot only express cheerfulness, they must also provide reassurance to distressed or upset customers by remaining calm and expressing empathy or sympathy (Brotheridge & Grandey, 2002). Customers who express anger expect service persons to apologize and extend help and/or compensation. Conversely, customers expressing delight and joy expect employees to reciprocate (Menon & Dubé, 2000). In short, emotional labor means that, rather than always smiling, service employees must adapt their displayed affect to their customers' expressed affect.

Employee sensitivity and reactivity to customers is organizationally important because customer affective displays offer cues about customer satisfaction (Fisher & Ashkanasy, 2000; Rafaeli et al., 2020; Yom-Tov et al., 2018). Customer expression of negative affect is viewed as a cue of dissatisfaction (Diefendorff & Gosserand, 2003) and a call for a change in employee behavior (Gabriel & Diefendorff, 2015). Such signals can prompt employees to modify their displayed affect from positivity ("service with a smile") to empathy.

The *emotional labor* argument suggests that service employees cannot express emotions that are unaligned with organizational requirements (Ashforth & Humphrey, 1993; Geddes & Callister, 2007; Rafaeli & Sutton, 1987). Neither emotional labor requirement allows employees to express inappropriate emotions (e.g., unhappiness, frustration). Thus, when employees encounter customer displays of emotions such as anger or disappointment, emotional labor prescribes displays of complementary emotions (Hareli & Rafaeli, 2008; Keltner & Haidt, 1999) to amend the situation and appease the customer. The requirement for employees to adapt their affective displays to customers received little empirical attention. As noted, this adaptation requires employees to monitor customers' affective displays and decide on an appropriate affective reaction. This is complicated work since service employees must both express positive affect, through surface or deep acting (Grandey, 2003), and gauge customers' affective displays.

Limited empirical research has demonstrated these relationships between customer and employee affective displays. For example, Gabriel and Diefendorff (2015) showed that customer affective displays shaped employee use of emotional labor strategies throughout simulated customer service interactions. Thus, we predict that employees will adapt their affective displays in response to customer affective cues. In other words, employees engage in Zaki and Williams' (2013) response-dependent regulation, with their responses relying on customer feedback.

Hypothesis 2. *Affective displays of service employees include displays that complement customer affective displays (i.e., employee response-dependent regulation).*

2.1.3. Customer Affective Displays and Emotion Regulation

Our first two hypotheses suggest that employees comply with emotional labor requirements by engaging in recurring acts of cheerfulness, a response-independent regulation process (Hypothesis 1), and also by attending to customers' affective displays, a response-dependent regulation process (Hypothesis 2). Customers and employees are partners in the same social interaction (McCallum & Harrison, 1985), but customers do not have emotional labor requirements; thus, they can use affective displays to convey what they please to their communication partner – the employee – with far fewer constraints (Grandey et al., 2010; Zablah et al., 2017). This situation, in which only one partner in the same interaction is subject to emotional labor, allows for a comparison of affective behaviors.

Customers who feel motivated to control their affect can express this to the service employee, thus engaging in intrinsic interpersonal regulation (Zaki & Williams, 2013). Sharing one's emotions with a service employee can, in turn, help regulate the customer's affect through either response-independent or response-dependent mechanisms. Expressing affect to an employee involves some form of labeling, which promotes emotion regulation (Kircanski et al., 2012; Torre & Lieberman, 2018), regardless of the employee's response (i.e., response-independent regulation). In contrast, response-dependent emotion regulation can occur when customers allow an employee's response to regulate their affect. For example, an employee's supportive displays might motivate customers to re-evaluate the situation in a way that makes them feel calm because they perceive that someone is handling their needs. Employees' signals might be more or less explicit, and may include pleasantries (e.g., "don't worry, I am taking care of it") or a reflection of the customer's expressions (e.g., "I know, this is really frustrating"), thus functioning to help customers regulate their emotions (Zaki & Williams, 2013).

Further, if, as emotional labor theory asserts, employees' positive affective displays lead to more satisfied customers (Pugh, 2001; Zapf, 2002), then positive employee messages should lead to more positive customer displayed affects. Some studies support this logic, demonstrating that employees' positive affective displays predict customers' emotions (Barger & Grandey, 2006; Pugh, 2001). These studies, however, measured *felt* affect, not displayed affect, and they measured affect at the *employee* level of analysis. Lacking more information about the customer perspective, we cannot formulate formal hypotheses regarding response-dependence or independence patterns in customers' affective displays. However, we can formulate predictions about differences between employees and customers regarding the enactment of their regulation processes.

2.1.4. Response-Independence vs. Dependence in Employee vs. Customer Affective Displays

Hypotheses 1 and 2 refer to the response-independence (i.e., intrapersonal) and dependence (i.e., interpersonal) patterns in employee affective displays. Next, we contend that customer affective displays are less response-dependent than employee affective displays, because customers have more power than employees (Rafaeli, 1989; Shamir, 1980). Customers' power over employees, as noted by Diefendorff and Greguras (2009) and by Grandey, Dickter, and Sin (2004), is evident in the popular mantra "the customer is always right." Customers are free to choose a service provider, while employees commit to an employer and must stay at a workstation. The power that a customer has is so glaring that frontline service roles have been named "subordinate" and "servile" roles (Shamir, 1980). Customers are also "free" because they presumably pay for service, which reinforces their power and enables them to impose demands on employees (Dormann & Zapf, 2004; Groth & Grandey, 2012).

Power is integral to the understanding of affective displays, because people with high power have more liberty to display what they choose, whereas people with low power are likely to be influenced by those with higher power (van Kleef et al., 2004; van Kleef & Lange, 2020). Moreover, people with low power tend to excel at understanding others, whereas people with high power often fail to reciprocate this attentiveness (Talaifar et al., 2020). Relatedly, people of lower social status display greater compassion for others (Stellar et al., 2012), more accurately judge the emotions of others (Kraus et al., 2010) and are better at inferring the emotional states of targets than their higher status counterparts (Dietze & Knowles, 2021). People with high power do not need, and are less motivated, to attend to low power people because they have more control over their own outcomes (Fiske, 1993). Thus, we expect that customers' affective displays to be self-focused, such that they do not consider employees' affective displays. This would suggest that customers' displayed affect manifests more independence than employees' affective displays. In contrast, we expect employees to pay more attention to customers' affective displays than vice versa, illustrating responsiveness to – or dependence on – customers.

The respective goals of customers and employees also sustain the power differences between them. The end goal for a customer is satisfaction; for employees, it is to satisfy customers. Thus, customers have more liberty than employees regarding the emotions they express (Grandey et al., 2010). Employees must be attuned to customer affective displays, whereas customers can ignore those of employees. There are no organizational consequences for customers who do not adapt their responses to employees' displays. In contrast, employees' behaviors are monitored and they can be reprimanded or penalized if a customer is upset because their emotional needs were not considered and attended to (Jones & Rittman, 2002). For employees, a failure to attend to customer affective displays can have wage consequences. In contrast, customers are likely to benefit from expressing emotions (e.g., Glikson et al., 2019).

In summary, customers' affective displays can be thought of as "inputs" which influence employees' supportive displays. Employees' emotional labor requirements and the power differences between employees and customers lead employees to adapt their responses to customer displays. Conversely, the higher power that customers enjoy allows them to retain independence in their regulatory focus.

Hypothesis 3. *Affective displays of customers are consistent with their own previous affective displays to a greater extent than affective displays of employees are consistent with their own previous affective displays (i.e., greater customer response-independence than employee response-independence).*

Hypothesis 4. *Affective displays of employees are adapted to their customer's affective displays to a greater extent than affective displays of customers are adapted to their employee's affective displays (i.e., greater employee response-dependence than customer response-dependence).*

2.2. The Current Research

We analyze written service interactions conducted through chat. Although computer-mediated and text-based interactions include relatively limited non-verbal cues (i.e., no facial or vocal cues), research shows that they demonstrate affective displays (see also Cheshin et al., 2011; for a review, see Derks et al., 2008; Hancock et al., 2007; Harris & Paradice, 2007), thus affording us a suitable platform for testing our predictions. In text-based customer service, however, both customers and employees can edit their text; therefore, written interactions can include planned affective displays, unlike face-to-face or voice interactions where individuals may not be able to “hide” or “fake” their feelings. Thus, text-based communication is less amenable to discerning dynamics of emotion contagion or mimicry because we observe only displays of affect, not genuine emotions.

In Study 1, we examine real-life customer-service interactions conducted through service chats on a corporate website. Such data offer a new venue for research on interpersonal interactions. Our analysis gauges affective displays using an automated assessment of customer and employee texts written during genuine service interactions. Study 1 provides assessments of affective displays for *each message in each interaction*. The analyses embrace and unpack the complexity of the emotional landscape of service interactions. Rather than aggregating data points, we study each affective display’s effects on the partner’s affect displayed in response. We test our hypotheses by examining the affective display patterns of employee messages *after* the receipt of customer messages, and the patterns of customer affective displays in messages *after* the receipt of employee messages.

Study 2 complements the Big Data analyses of Study 1 by creating and analyzing a pool of simulated service interactions about a specific, controlled topic. Study 2.1 creates the pool of interactions. Study 2.2 asks independent raters to rate displays of discrete emotions in each employee and customer message to further assess Hypotheses 1 and 2. Study 2.3 asks independent raters to judge interactions in terms of the response-independence and response-dependence of employees’ and customers’ responses to further assess Hypotheses 3 and 4. Lastly, Study 2.4 examines the effects of employee response-dependent affective behaviors on customer outcomes. Together, the four studies offer experimentally controlled tests of our hypotheses.

2.3. Study 1

2.3.1. Method

2.3.1.1 Research Context and Data

Study 1 tested our hypotheses by analyzing data we received from LivePerson Inc. (http://www.liveperson.com/). We analyzed data from 164,899 real-life service interactions between customers and employees of an airline company over 14 months (March 2016 to April 2017). All interactions were conducted in writing through an online chat platform that customers access from brands' websites and employees reach from their employer's contact center. The service interactions we analyzed involved 57 employees, with approximately half held before 3 PM and half after 3 PM.

The data comprise 1,320,392 customer and employee messages. Full interactions include between two messages and several hundred messages. The mean number of customer messages in an interaction is 5.40 (*SD* = 3.76), and the mean number of employee messages is 5.78 (*SD* = 3.70). Messages automatically generated by the platform (e.g., "Thank you for your patience. One of our agents will be with you shortly.") were not included in our analyses.

The Study 1 data include documentation of the interaction from when a customer begins to converse with an employee until the interaction ends. Figure 8 illustrates a typical service interaction. Each message in the dataset is identified by date, time, ID, and author (customer or agent). To ensure anonymity and customers' and employees' privacy, the message texts remained only on the company's IT system and were not part of our data. The company enabled us to obtain nonobtrusive operational measures of our research variables, including customer and employee affective displays. Our analysis is based only on objective data archived during service interactions; we do not have access to customers or employees for interviews or surveys.

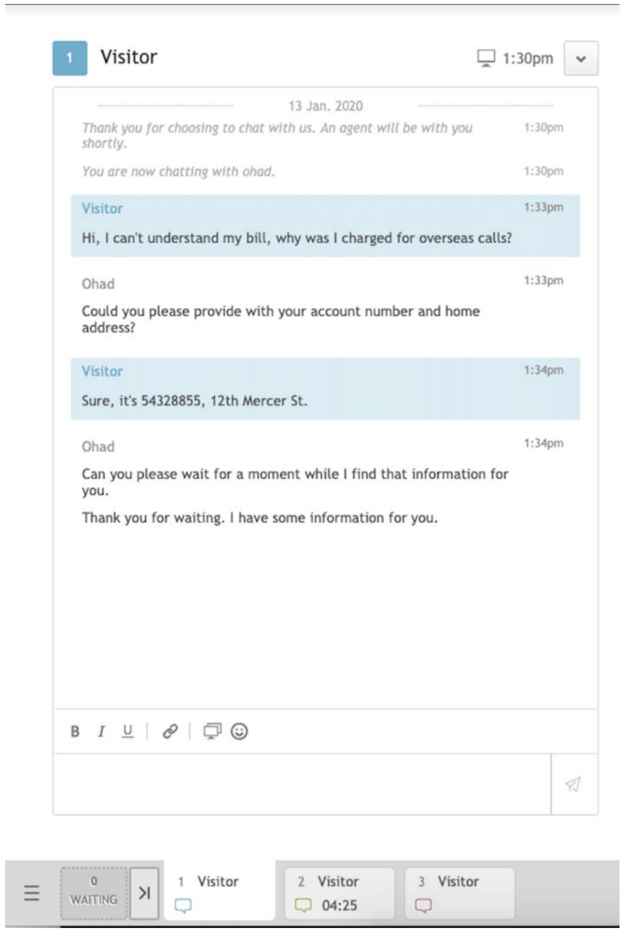

Figure 8.
Snapshot of a service interaction between a service employee (Ohad) and an (anonymized) customer

2.3.2. Analyses and Variables

Following the Actor-Partner Interdependence Model (APIM; Kenny et al., 2006), we incorporate the affective displays of both partners to a service interaction into a single analytical approach (Thorson et al., 2018). Since employee and customer messages are nested within interactions, there is potential interdependence of the observations, thus APIM treats employee and customer messages as nested within interactions while retaining them as the unit of analysis. Specifically, we utilize the stability and influence model, a special case of APIM (see Figure 9, Thorson et al., 2018) to account for the affective display measures having been collected from two partners of a dyad repeatedly over time (throughout the service interaction).

In our model, the actor effect is a stability path, in which a participant's affective display score in one message (i.e., at one time point) is treated as a function of their affective display score in their own previous message (i.e., at a prior time point). In parallel, the partner effect is an influence path in which the participant's affective display score in the current message is treated as a function of the partner's affective display score in their most recent message. The analyses use the SAS multilevel modeling approach (Kenny et al., 2006), with the PROC MIXED syntax and fixed and random effects, as Thorson et al. (2018) recommend.

2.3.2.1.1 Actor Variables

Each message in our dataset was written by either an employee or a customer, defined by two dummy variables, ***Employee*** (coded 1 for an employee message, 0 otherwise) and ***Customer*** (coded 1 for a customer message, 0 otherwise). An effect-coded variable ***Actor*** (employee message is coded as +1, customer message is coded as -1) allowed a test of Hypotheses 3 and 4 regarding differences in response-independent (i.e., actor) and response-dependent (i.e., partner) affective behaviors between employees and customers.

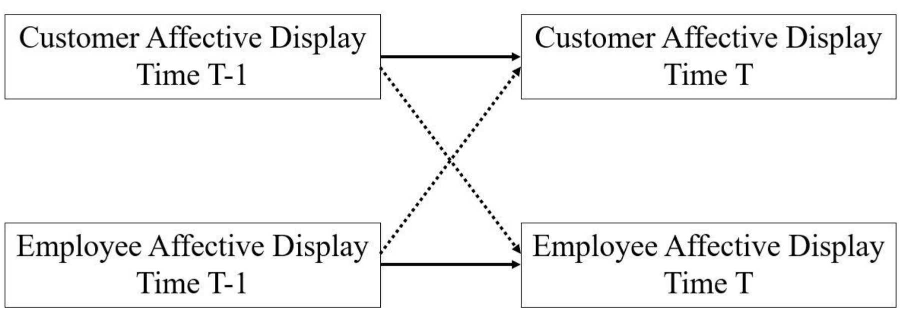

Figure 9.
The Actor-Partner Interdependence Model. The solid lines represent the response-independence, actor effects (the intrapersonal paths), in which an actor's affective display at one time point predicts their own affective display at a later point. The dashed lines represent the response-dependence, partner effects (the interpersonal paths), in which a partner's affective display at one time point predicts the actor's later affective display.

2.3.2.1.2 Affective Display Variables

We assessed employee and customer affective displays in each message using SentiStrength, an automated sentiment analysis tool that was discussed in Paper 1 of this dissertation (Thelwall, 2017; Yom-Tov et al., 2018) . Thus, we use a bipolar measure of affective displays, with negative (positive) scores indicating negative (positive) affective displays. For brevity, we use the term ***Actor Display*** in referring to the affect displayed by the actor (i.e., employee or customer) in a focal message. We use ***Actor Display Lag*** and ***Partner Display Lag*** for the affective displays in the previous messages of the actor and partner, respectively. These variables are operationally defined as the SentiStrength scores assigned to the corresponding message.

2.3.2.1.3 Control Variables

We control for multiple variables that may influence the affective displays. We control for workload, since, as Sutton and Rafaeli (1988) showed, under a higher workload, employees and customers assume different types of expressions are appropriate. Text length is controlled since it reflects the problem’s complexity and the effort required to solve it, and relates to customer affective displays (Altman et al., 2020; Yom-Tov et al., 2017). Response time is controlled, since it can influence the wait time of employees and customers (Maister, 1984; Yom-Tov et al., 2017). Hence, for each time point of a message in which an affective score was calculated, we also calculated the following variables: (a) ***Current Customer Workload,*** defined as the number of customers waiting for service at the time of a focal message; (b) ***Current Employee Workload,*** the number of customers an employee handles at the time of a focal message; (c) ***Length of Partner Message,*** the number of words written in the partner message prior to a focal message; (d) ***Partner Response Time*** (to the actor), the time elapsed between a previous actor message and the previous partner message. Table 1 describes the study variables; Table 2 presents the means, standard deviations, and inter-correlations between study variables.

2.3.3. Results

Our results report several models. Model 1.1 is a basic model that estimates employees' response-independence (i.e., actor) and dependence (i.e., partner) patterns, testing Hypotheses 1 and 2. Model 1.1 includes exploratory analyses of *customer* response-independence and dependence patterns; we could not formulate formal hypotheses regarding those but believe they should not be neglected. Model 1.2 examines Model 1.1 with control variables. Model 2.1 elaborates Model 1.1 to consider the actor (employee vs. customer) as a moderator to directly test the difference between employee and customer effects suggested in Hypotheses 3 and 4. Model 2.2 examines Model 2.1 including control variables.[1]

2.3.3.1 Effects on Employee and Customer Affective Displays

Table 3 presents the results for the fixed effects of Models 1.1 and 1.2, showing overall significant positive affect displayed by employees and customers (β=0.525, p<.001 and β=0.419, p<.001, respectively). The tests of response-independence, or actor effects, are the stability slopes ("Employee X Actor Display Lag" and "Customer X Actor Display Lag"), which indicate a response-independence (an actor effect) for both employees and customers[2] (β=0.094, p<.001 and β=0.148, p<.001, respectively). On average, a one-point increase in customer affective score leads to an increase of 0.15 points in their subsequent message's affective score. Similarly, an

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[1] We note we could not form hypotheses about the unfolding of affect over time as we could not find relevant research except for very broad and very recent observations (Rafaeli et al, 2020). Although not in our hypotheses, we also tested Model 2.1 with the location of a message in the interaction (i.e., location=1 for the first message, location=2 for the second, etc.) to test whether timing of a message within an interaction moderates the predicted effects. While adding the location improved the model, the moderation effects were smaller than 0.01, implying negligible effects. For brevity, we do not report these analyses in full. They can be obtained from the first author.

[2] A significant interaction here means that higher values of actor affective display in one message are associated with higher values of the same actor affective display in the following message.

increase of one point in employee affective score leads to an increase of 0.1 point in their subsequent message's affective score.

The test for response-dependence, or partner effect, of employees is the influence slope "Employee X Partner Display Lag," which indicates a response-dependence (partner-focus) for employees, supporting our H2. Higher values of customer affective display in one message are associated with higher values of the employee affective display in the subsequent message (β=0.276, p<.001). On average, a one-point increase in customer affective score leads to an increase of almost 0.3 points in employee affective score in the subsequent message. In contrast, there is a negligible, though significant, response-dependence (partner effect) of customers: the influence slope "Customer X Partner Display Lag" indicates that for customers, higher values of employee affective display in one message are *statistically, but not practically,* associated with lower values of customer affective display in the subsequent message (β=-0.016, p<.001). Model 1.2 shows that all these effects remain similar and significant in the presence of the control variables, further supporting Hypotheses 1 and 2.

2.3.3.2 Response-Independence and Dependence in Employee and Customer Affective Displays

Hypotheses 3 and 4 suggest that response-independence and dependence differ between employees and customers. Specifically, because employees have less power in the interaction, we predicted that the response-independence (actor effect) will be stronger for customers (H3) while response-dependence (partner effect) will be stronger for employees (H4). Models 1.1 and 1.2 cannot compare the fixed actor and partner effects of employees and customers. Models 2.1 and 2.2 in Table 4 test these two predictions by including a main effect of message actor (binary variable, employee coded +1, customer -1) and interactions of this variable with the actor and partner display lags. We test whether the stability and influence slopes significantly differ between employees and customers.

The coefficient of the response-independence, actor effect (stability slope “Actor X Actor Display Lag”) confirms lesser employees' response-independence than customers’ (β=-0.055, p<.001), supporting Hypothesis 3. The coefficient of the response-dependence, partner effect (influence slope “Actor X Partner Display Lag”) indicates more response-dependence of employees than customers (β=0.292, p<.001), supporting Hypothesis 4. All effects remain similar and significant with control variables (see Model 2.2), further supporting H3 and H4.

2.3.4. Study 1 Summary

Study 1 tested and supported the four hypotheses we posited regarding response-independence and dependence in affective behaviors of service employees and customers by assessing predicted effects in a natural environment with large-scale data of actual employee and customer interactions. Study 1 relied on automated sentiment analysis to code the affective displays. We could not control for the topic of the interactions. As described next, Study 2 examined the hypotheses developed and tested in Study 1 in a controlled environment, where the topic of interactions was known and controlled, and affective displays were coded by human raters. Study 2 also provided exploratory analyses of the hypotheses with discrete emotions.

Table 1.

Study 1 Description of study variables

Variable	Description of variable
Employee	Coded 0 for focal customer message and 1 for focal employee message
Customer	Coded 0 for focal employee message and 1 for focal customer message
Actor	Coded -1 for focal customer message and 1 for focal employee message
Actor Display	Affect score for focal actor message based on sentiment analysis tool
Actor Display Lag	Affect score for previous (most recent) actor message based on sentiment analysis tool
Partner Display Lag	Affect score for previous (most recent) partner message based on sentiment analysis tool
Current Customer Workload	Number of customers waiting for service at time of focal message
Current Employee Workload	Number of customers the employee handles at the time of focal message
Partner Length of Message	Number of words a partner wrote in previous message
Partner Response Time	Time elapsed between the previous (most recent) actor message and previous (most recent) partner message

Table 2.

Study 1 Means, standard deviations, and intercorrelations of study variables

Variable	Mean	Std. Deviation	1	2	3	4	5	6
1 Actor Display	0.441	0.928	-					
2 Actor Display Lag	-0.075	0.909	.125**	-				
3 Partner Display Lag	-0.042	0.912	.103**	.031**	-			
4 Current Customer Workload	2.210	2.798	.008**	.004**	.005**	-		
5 Current Employee Workload	2.294	0.733	.019**	.038**	.032**	.178**	-	
6 Partner Length of Message	16.583	13.301	-.063**	-.081**	.004**	.013**	.013**	-
7 Partner Response Time	48.407	41.037	-.033**	-.008**	-.081**	.013**	.047**	.221**

N =1,320,392. **. Correlation is significant at the 0.01 level (2-tailed).

Table 3.

Study 1 Fixed effects estimates for predicting focal affective display

	Model 1.1				Model 1.2			
	B	SE	Lower CI	Upper CI	B	SE	Lower CI	Upper CI
Employee	0.525 ***	0.001	0.523	0.528	0.508 ***	0.003	0.502	0.514
Customer	0.419 ***	0.001	0.417	0.421	0.406 ***	0.003	0.400	0.413
Employee X Actor Display Lag	0.094 ***	0.001	0.091	0.096	0.093 ***	0.001	0.091	0.096
Customer X Actor Display Lag	0.148 ***	0.002	0.145	0.151	0.147 ***	0.002	0.144	0.150
Employee X Partner Display Lag	0.276 ***	0.002	0.273	0.280	0.274 ***	0.002	0.271	0.278
Customer X Partner Display Lag	-0.016 ***	0.001	-0.018	-0.014	-0.017 ***	0.001	-0.018	-0.015
Current Customer Workload					0.002 ***	0.000	0.001	0.002
Current Employee Workload					0.013 ***	0.001	0.011	0.015
Partner Length of Message					-0.001 ***	0.000	-0.001	0.000
Partner Response Time					0.000 ***	0.000	0.000	0.000
AIC	3431054				3430631			
-2 log likelihood	3431012				3430581			

Dependent variable: Actor Display.

Employee is coded as 0 for focal customer message and 1 for focal employee message.

Customer is coded as 0 for focal employee message and 1 for focal customer message

N=164,899 service interactions (Level 2); *n*=1,320,392 messages (Level 1).

*** $p < .001$

Table 4.

Study 1 Fixed effects estimates for predicting focal affective display with actor as a moderator

	Model 2.1				Model 2.2			
	B	SE	Lower CI	Upper CI	B	SE	Lower CI	Upper CI
Intercept	0.419 ***	0.001	0.417	0.421	0.406 ***	0.003	0.400	0.413
Actor Display Lag	0.148 ***	0.002	0.145	0.151	0.147 ***	0.002	0.144	0.150
Partner Display Lag	-0.016 ***	0.001	-0.018	-0.014	-0.017 ***	0.001	-0.018	-0.015
Actor	0.106 ***	0.002	0.103	0.109	0.101 ***	0.002	0.098	0.105
Actor X Actor Display Lag	-0.055 ***	0.002	-0.058	-0.051	-0.054 ***	0.002	-0.057	-0.050
Actor X Partner Display Lag	0.292 ***	0.002	0.288	0.296	0.291 ***	0.002	0.287	0.295
Current Customer Workload					0.002 ***	0.000	0.001	0.002
Current Employee Workload					0.013 ***	0.001	0.011	0.015
Partner Length of Message					-0.001 ***	0.000	-0.001	0.000
Partner Response Time					0.000 ***	0.000	0.000	0.000
AIC	3431054				3430631			
-2 log likelihood	3431012				3430581			

Dependent variable: Actor Display.

Actor is coded as -1 for focal customer message and 1 for focal employee message.

N=164,899 service interactions (Level 2); *n*=1,320,392 messages (Level 1).

*** $p < .001$

2.4. Study 2

Study 2 comprised four interdependent studies. Study 2.1 created a pool of customer service interactions using a text-based service simulation. Participants were randomly assigned to the role of either a customer or employee and interacted with a partner. Study 2.2 and 2.3, respectively, recruited two separate sets of independent naïve judges to rate the presence of discrete emotions and response-independence and dependence in the messages collected in Study 2.1. All studies were conducted using an online platform (Prolific). Participants were screened for being native English speakers and were reimbursed for their participation. Study 2.4 utilized ratings collected in Studies 2.1-2.3 to examine the influence of employee affective behaviors on customer outcomes.

2.4.1. Study 2.1 Generating a sample of service interactions

Study 2.1 participants (*n*=268) were randomly assigned to a condition asking them to play the role of either customer or service agent, both of a firm that provides delivery services to multiple brands through chat. Participants were asked to interact with a partner playing the other role. The interaction was in writing using a tool that simulates text-based interactions (Chatplat, https://www.chatplat.com/; Blunden et al., 2019; Brooks & Schweitzer, 2011; Huang et al., 2017; Lee et al., 2018; Wolf et al., 2016). Participants were told the study goal was to learn how customers (or agents) would respond in a service interaction. The study started with an illustration of an interaction, followed by the role-playing instructions. Customer instructions were as follows:

> *“In playing the customer, imagine that you purchased a new tablet two weeks ago, and it arrived with a defective screen that cannot be used. Please present your issue to the service agent.”*

Employee instructions were designed to simulate instructions typically given to service employees, so were as follows:

> *"In playing the service employee, remember to be respectful to the customer. Begin by introducing yourself ("My name is ____ and I am happy to serve you") and continue as you see fit."*

Interaction time was limited to 10 minutes to avoid lengthy interactions. Participants were told to end the interaction when they felt the issue had been settled and in no more than 10 minutes. To ensure motivation, we offered triple compensation to customers who did the best and most realistic job communicating their issue and to employees who received the highest evaluations by their partners.

After receiving their role description, each interaction member continued to the chat platform which randomly paired participants of the two roles. The platform recorded the interaction and enforced the time limit. If the interaction was not complete after nine minutes, the partners received a message that one minute was left. After the interaction ended, participants were asked to indicate the role they played (i.e., customer, service agent, or neither) as a manipulation check and were asked for basic demographic information. Participants in the customer role were asked to rate the service employee, by responding to two items: "I would like to receive service from this agent again", "I am satisfied with the service that the agent provided", on a 7-point scale (1 = "not at all" to 7 = "very much").

We read all 134 interactions to confirm that participants played their respective role and removed four interactions where participants did not converse about the relevant topic. We also removed 28 interactions which had not been completed (because of a technical problem, the time limitation, or a partner leaving before completing), yielding a final sample of 102 valid interactions (average number of messages in an interaction was 16.036, *SD*=8.917). The goal of collecting these interactions was to obtain stimuli for subsequent studies.

2.4.2. Study 2.2 Response-Independence and Dependence in discrete-emotion expressions

Our theory posited dynamics of affective displays in dyadic service interactions. Study 1 tested and supported our hypotheses with general positive and negative affective displays. Although the automated sentiment analysis tool used in Study 1 did not avail reliable analyses of discrete emotions, theory and research repeatedly call for a focus on specific emotions. Study 2.2 thus further uses the controlled interactions collected in Study 2.1 to explore potential associations between discrete emotions expressed by employees and customers. As our primary interest is in employees' emotional labor requirements, Study 2.2 examines only effects of customer discrete emotions on those of employees (Hypotheses 1 and 2).

We limited the set of emotions to five emotions that often appear in service situations in order to retain participant attention and focus (L. L. Berry, 1999). First, we chose anger because customer displays of anger are highly prevalent in service interactions, with employees reporting that 15-20% of their interactions per day comprise verbally aggressive displays (Grandey et al., 2004). We added happiness since employees are expected to suppress displays of anger, and display happiness in their interactions with customers (Grandey et al., 2010). We further added disappointment, as this emotion leads to customer dissatisfaction and complaining (Mattila & Ro, 2008; Zeelenberg & Pieters, 1999, 2004). Finally, we added sadness and empathy. Sadness, a prevalent human emotion (although to a lesser extent than anger and happiness, .e.g., Scherer, 2004; Scherer et al., 2004), is frequently expressed by service employees in phrases such as "I am so sorry" (Scherer, 2005), and is known to influence customer service outcomes (Cheshin et al., 2018). Additionally, empathy is frequently endorsed as fundamental to service delivery (Bove, 2019; Varca, 2007).

Thus, we adapted Hypothesis 1 to focus on discrete emotion terms:

Hypothesis 5. *Employee affective displays include recurring displays of happiness (employee response-independent regulation).*

A modification of Hypothesis 2 to emphasize discrete emotion terms, suggests two hypotheses:

Hypothesis 6. *Customer displays of happiness increase employee displays of happiness (employee response-dependent regulation).*

Hypothesis 7. *Customer displays of anger, disappointment, or sadness reduce employee displays of happiness (employee response-dependent regulation).*

A related question regards which emotions employees display in response to customer displays of anger, disappointment, or sadness. We could not find sufficient literature to support distinct predictions for each of these discrete emotions, thus, we extend Hypothesis 2 as follows:

Hypothesis 8. *Customer displays of anger, disappointment, or sadness increase employee displays of empathy or sadness (employee response-dependent regulation).*

2.4.2.1 Procedure and Measures

Participants were shown a series of messages that were randomly extracted from the 897 employee messages and 867 customer messages from the interactions collected in Study 2.1. After reading each message, participants rated the extent to which it expressed each of the five emotions (happiness, anger, disappointment, sadness, and empathy) on a 5-point scale (0 = “not at all” to 4 = “very much”). Participants also indicated which of the discrete emotions was most dominant in each message by choosing from the following options: one of the five emotions, “some other emotion”, or “no emotion.” Participants only read and rated the specific messages to which they were assigned and were not aware of who wrote the message (i.e., employee or customer) or any other information about the interaction. Thus, each message in an interaction was rated by a different set of participants, eliminating the risk of same-source bias. We collected three ratings for each message and eliminated participants who did not pass an attention check, resulting in a final sample of 517 (54% female, mean age = 32).

2.4.2.2 Results

First, we examined the dominant emotions indicated by the raters only for messages with consensus between the three raters. In employee messages, the most dominant emotion was empathy (64.8%), followed by happiness (19.2%) and no emotion (16%). The most dominant customer emotion was disappointment (42.1%), followed by happiness (40%), no emotion (15.2%), and anger (2.1%). In only two of the initial 1764 employee and customer messages did all three raters agree that another discrete emotion (not included on our list) was most dominant, but they did not agree on which emotion it was. This led us to trust that our list of discrete emotions was exhaustive in the context of our interactions.

Second, to ensure that it was appropriate to aggregate ratings, we computed intraclass correlation coefficients (ICC; Bliese, 2000) across each of the three ratings. Only employee happiness and empathy, and customer happiness, anger, disappointment, and sadness reached acceptable values for aggregation (0.561-0.814, see Table 5); thus, we focused our subsequent analyses on these emotions. Table 6 presents the means, standard deviations, and inter-correlations between study variables.

Before running regression analyses, we examined inter-correlations among rated emotions and found very high correlations between customer anger, disappointment, and sadness (0.736-0.823, see Table 6). We ran a principal components analysis (PCA) with Varimax rotation to examine whether these three distinct emotion variables loaded on the same component. The overall Kaiser-Meyer-Olkin (KMO) measure was 0.745, individual KMO measures were all greater than 0.7, and Bartlett's Test of Sphericity was statistically significant [$\chi^2(3) = 1021.523$, $p<0.0005$], all indicating suitability for a PCA. The PCA revealed only one component with an eigenvalue greater than one, which explained 84.575% of the total variance. The scree plot also suggested that only one component should be retained. Thus, the following analyses include only one customer variable, disappointment,[3] which had the highest rater agreement and was most frequently selected as the dominant customer emotion (Table 5).

Finally, we used regression to test the response-independence and dependence predicted by Hypotheses 1 and 2 in discrete emotion terms. The first regression, predicting *employee happiness* (Model 3.1, Table 7), tested and confirmed an *employee response-independence*, supporting Hypothesis 5: Previous employee happiness positively predicted employee happiness in a focal message. It also confirmed an *employee response-dependence* (Hypotheses 6 and 7): Customer happiness positively predicted employee happiness, whereas customer disappointment negatively predicted employee happiness. The second regression analysis, predicting *employee empathy* (Model 3.2, Table 7), supported Hypothesis 8: Customer disappointment positively predicted employee empathy. Both analyses controlled for previous customer and employee expressions of emotion. These results indicate that employees adapt emotion displays to customers, and display a strong tendency for response-dependence, similar to Study 1.

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[3] Although we report only analyses using customer disappointment, we also ran analyses using customer anger, customer sadness, the average of all three variables, and the component score. All analyses revealed similar results to those reported for customer disappointment.

Table 5.
Study 2.2 Intraclass correlations (ICC) and frequency of dominant emotions

Emotion	**Intraclass Correlations**		**% Dominant Emotion**	
	Employee	Customer	Employee	Customer
Happiness	**0.640**	**0.814**	0.192	0.400
Anger	0.317	**0.561**		0.021
Disappointment	0.383	**0.790**		0.421
Sadness	0.429	**0.601**		
Empathy	**0.573**	0.305	0.648	
Some other emotion	-	-		0.007
No emotion	-	-	0.160	0.152

Table 6.
Study 2.2 Means, standard deviations, and intercorrelations of study variables

	Variable	**Mean**	**Std. Deviation**	**1**	**2**	**3**	**4**	**5**
1	Employee Happiness	1.238	1.038	-				
2	Employee Empathy	1.763	1.031	.053	-			
3	Customer Happiness	1.160	1.142	.406**	-.030	-		
4	Customer Anger	0.699	0.784	-.257**	.129**	-.464**	-	
5	Customer Disappointment	1.207	1.175	-.334**	.296**	-.526**	.745**	-
6	Customer Sadness	0.756	0.806	-.279**	.267**	-.444**	.736**	.823**

**. Correlation is significant at the 0.01 level (2-tailed).

Table 7.
Study 2.2 Regressions predicting employee discrete emotions

	β		SE	Lower CI	Upper CI
Model 3.1- Predicting Employee Happiness					
Constant	0.917	***	0.117	0.686	1.147
Employee Previous Happiness (H5)	0.154	***	0.046	0.064	0.244
Employee Previous Empathy	0.032		0.040	-0.045	0.110
Customer Happiness (H6)	0.262	***	0.044	0.176	0.348
Customer Disappointment (H7)	-0.176	***	0.042	-0.259	-0.092
R-squared			0.205		
Model 3.2- Predicting Employee Empathy					
Constant	1.240	***	0.123	0.998	1.482
Employee Previous Happiness	0.010		0.048	-0.084	0.104
Employee Previous Empathy	-0.052		0.042	-0.134	0.030
Customer Happiness	0.164	***	0.046	0.074	0.254
Customer Disappointment (H8)	0.340	***	0.045	0.252	0.427
R-squared			0.112		

N=500 employee messages. *** $p < .001$

2.4.2.3 Study 2.2 Summary

Study 2.2 complements Study 1 results by examining employees' response-independence and dependence in discrete emotions expressed at the message level. The findings indicate that employees' discrete emotions are consistently related to customers' previous discrete emotions. We believe that these patterns provide support for Hypotheses 1 and 2 (adjusted for discrete emotions in Hypotheses 5-8) by demonstrating employee response-independence and dependence in discrete emotion terms.

The high correlations between customer anger, disappointment, and sadness found in Study 2.2 may be because participants serially rated five discrete emotions. The low correlations between the three emotions and the other two confirm that participants did not mindlessly report all discrete emotions as similar, rather it appears that they recognized some emotions as distinct but not others. Moreover, this task was a realistic depiction of service interactions, wherein employees and customers have only a few seconds and succinct messages to discern expressed emotions. The high correlations suggest a general component of negatively-valenced emotions.

2.4.3. Study 2.3 Response-Independence vs. Dependence in full service interactions

The goal of Study 2.3 was to compare human ratings of the response-independence and dependence in affective displays of employees and customers (i.e., examining Hypotheses 3 and 4) in Study 2.1, at a broader view, focusing on *full* interactions. Participants (*n*=691) were randomly assigned to rate either the employee or the customer in an interaction, which they were asked to read in full. They rated the person's response-independence and dependence.

2.4.3.1 Measures

Participants rated response-dependence on two-items (of employee or customer): (i) "The [person] attended to emotions that the [other person] expressed;" (ii) "the [person] responded to the emotions that the [other person] expressed." Two other items assessed response-independence: (i) "The [person] expressed more or less the same emotions within the interaction;" (ii) "The [person] did not change the emotions expressed within the interaction." The final sample (after filtering for attention ("please choose six") and for completing the task in less than 30 seconds) was 657 (60% female, average age 32).

2.4.3.2 Results

As customary in using crowdsourcing data, we collected multiple ratings of each interaction (Alonso, 2019; Peer et al., 2017); three participants rated each customer and three different participants rated the employee in the same interaction to eliminate risk of same-source biases. To ensure appropriateness of aggregating ratings to the interaction level, we computed intra-class correlations (ICC; Bliese, 2000). The ICC values were small (-0.041-0.571), so we computed r_{wg} values for each interaction separately (LeBreton & Senter, 2008). After removing observations with r_{wg} of zero, suggesting no agreement between the three raters, the average ICC values were higher and acceptable (0.673-0.863, see Table 8 for ICC values in the full dataset and the subset), allowing rating aggregation (LeBreton & Senter, 2008). Cronbach's Alpha of the two-item measures were also satisfactory (response-independence: 0.829 and 0.856, response-dependence: 0.916 and 0.749, for employee and customer ratings, respectively). Thus, we averaged the items for each scale and actor separately, yielding the variables analyzed in Study 2.3, as Table 9 summarizes.

Table 8.
Study 2.3 Intraclass correlations (ICC) in the full dataset and in the subset

Item			Full dataset		Subset	
			ICC	(N)	ICC	(N)
Response-Independence						
	Employee	did not change the emotions expressed within the interaction	0.265	(97)	0.863	(47)
		expressed more or less the same emotions within interaction	0.030	(97)	0.673	(55)
	Customer	did not change the emotions expressed within the interaction	-0.041	(99)	0.813	(36)
		expressed more or less the same emotions within interaction	0.146	(99)	0.787	(48)
Response-Dependence						
	Employee	attended to the emotions that the (partner) expressed	0.529	(97)	0.722	(77)
		responded to the emotions that the (partner) expressed	0.571	(97)	0.748	(72)
	Customer	attended to the emotions that the (partner) expressed	0.015	(99)	0.693	(49)
		responded to the emotions that the (partner) expressed	0.272	(99)	0.681	(64)

Table 9.
Study 2.3 Means, standard deviations, and intercorrelations of study variables

Variable		Mean	Std. Deviation	1	2	3
1	Employee Response-Independence	5.008	1.194	-		
2	Customer Response-Independence	5.133	1.067	.237	-	
3	Employee Response-Dependence	5.372	1.071	.244	-.255	-
4	Customer Response-Dependence	4.644	0.937	.365*	.025	-.005

For a second test of Hypotheses 3 and 4, we conducted a repeated measure multivariate analysis of variance (MANOVA) with response-dependence and response-independence as dependent variables. The "within" factor was the actor (employee or customer). The analyses supported an actor effect (Wilks' Lambda $F(2,28)=4.080$, $p=0.028$, partial $\eta^2=0.226$), indicating a difference in the response-independence and response-dependence between employees and customers. Univariate analyses did not find employees as less response-independent ($M=5.008$, $SD=0.218$) than customers ($M=5.133$, $SD=0.195$, $F(1)=0.238$, $p=0.628$, partial $\eta^2=0.008$) but did confirm employees as more response-dependent to customers ($M=5.372$, $SD=0.196$) than customers to employees ($M=4.644$, $SD=0.171$, $F(1)=7.807$, $p=0.009$, partial $\eta^2=0.212$). Thus, the analyses could not further support Hypothesis 3 but did further support Hypothesis 4.

2.4.3.3 Study 2.3 Summary

Study 2.3 offered support, in a controlled environment, of Hypothesis 4, confirming greater response-dependence by employees than by customers, but did not support the greater response-independence of customers predicted in Hypothesis 3. The difference from Study 1 may be due to the controlled environment, small sample size, or the non-genuine interactions.

2.4.4. Study 2.4 Do employee affective behaviors improve customer outcomes?

Extrinsic interpersonal emotion regulation is intended to change the emotions and experiences of an interaction partner (Niven et al., 2009; Zaki & Williams, 2013). Specifically, emotional labor requirements are intended to lead to positive customer outcomes (Diefendorff & Gosserand, 2003). As Niven et al. (2009) described, employees use various strategies to improve customer affect; employees can create positive customer engagement with their own situation or convey acceptance of the customer's emotions to validate their experience. Employee behaviors, such as listening to a customer, allowing customers to vent, conveying care for the customer, or making the customer feel special, can all improve customer affect and thus are likely to improve customer satisfaction and related outcomes. All these behaviors can be categorized as response-dependent regulation behaviors, suggesting that employee response-dependent behaviors aid in promoting service delivery goals.

Our results thus far suggest that employees tend to adjust their affective displays to customers, thus enacting response-dependent emotion regulation. Our final analyses examine the effects of employee response-dependent displays following customer expressions of disappointment on customer outcomes. We focus on customer disappointment because it is challenging to employees (Zeelenberg & Pieters, 1999), requiring employees to adjust their expressed affect in order to positively influence a customer's end affective state. Study 2.2 showed that employees respond to customer disappointment with displays of empathy. In this study, we posit that employee expressions of empathy, in turn, lead to more displayed happiness and less disappointment by customers. Research on customer expectations regarding employee responsiveness to their disappointment (Menon & Dubé, 2000), leads us to posit that employee response-dependence can mitigate the basic negative effect of customer disappointment on customer satisfaction (Zeelenberg & Pieters, 1999). Hence, our final hypotheses:

Hypothesis 9. *Customer displays of disappointment increase employee displays of empathy (employee response-dependent regulation), which in turn reduce customer displays of disappointment.*

Hypothesis 10. *Customer displays of disappointment increase employee displays of empathy (employee response-dependent regulation), which in turn increase customer displays of happiness.*

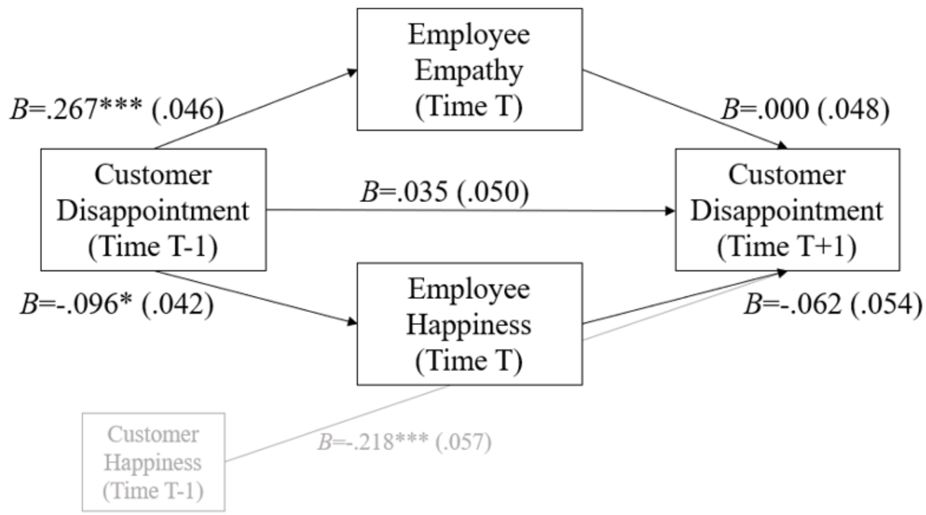
Hypothesis 11. *Employee response-dependent regulation* <u>*mitigates*</u> *the negative effect of customer displays of disappointment on customer satisfaction.*

2.4.4.1 Analyses and Results

2.4.4.1.1 Message Level Analyses and Results

To test Hypotheses 9 and 10, we conducted bootstrap analyses with 5000 samples (SPSS Macro PROCESS, Model 4; Hayes, 2017); customer disappointment at time T-1 was the IV and employee empathy at time T was the mediator. Model 4.1 presents customer disappointment at time T+1 as the DV, whereas Model 4.2 presents customer happiness at time T+1 as the DV (see Figure 10 and Figure 11, respectively). In both models, we added customer happiness at time T-1 as a control variable and employee happiness at time T as an additional mediator.

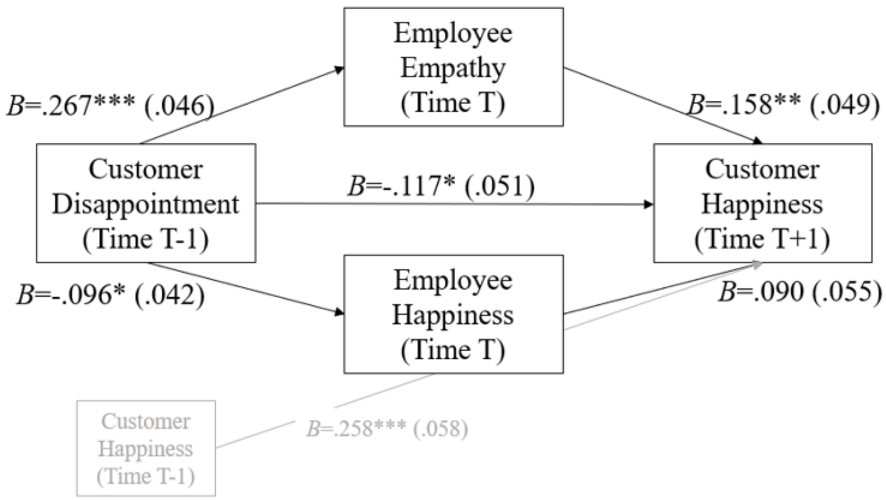
Hypothesis 9 states that customer displays of disappointment increase employee displays of empathy, which in turn reduce customers' subsequent displays of disappointment. As can be seen in Model 4.1 (Figure 10), the 95% confidence interval of the indirect effect of customer disappointment (T-1) on subsequent customer disappointment (T+1) through employee empathy (T) includes zero (*indirect effect*=0, *SE*=.013; 95%*C.I.*=[-.027,.027]). This suggests that employee empathy does not mediate the relationship between customer displays of disappointment; thus, Hypothesis 9 was not supported. We also did not find evidence of mediation through employee happiness (*indirect effect*=.006, *SE*=.006; 95%*C.I.*=[-.004,.019]). There was no significant relationship between prior customer displays of disappointment and subsequent displays of customer disappointment (*total effect*=.041, *p*=.400). This suggests that customers are not consistent in their displays of disappointment, which may partially explain why employee empathy does not improve or reduce customer disappointment.



Indirect effect through employee empathy = .000 (.013), 95% C.I. [-.027,.027].
Indirect effect through employee happiness = .006 (.006), 95% C.I. [-.004,.019].
N=475 employee messages, R^2=.067. * $p < .05$, ** $p < .01$, *** $p < .001$.
Numbers in parentheses represent standard errors.
Customer happiness at T-1 is included as a control.

Figure 10.
Employee empathy does not mediate a change in customer disappointment.

Hypothesis 10 was supported: Customer disappointment increased employee displays of empathy, which in turn increased customer displays of happiness. Model 4.2 (Figure 11) shows that the 95% confidence interval of the indirect effect of customer disappointment (T-1) on subsequent customer happiness (T+1) through employee empathy (T) does not include zero (*indirect effect*=.042, *SE*=.015; 95%*C.I.*=[.015,.074]). Thus, employee empathy mediates the relationship between customer displays of disappointment and subsequent customer happiness. Higher customer disappointment leads to higher employee empathy (*a*=.267, *p*<.001), and as employee empathy increases, subsequent customer happiness increases (*b*=.158, *p*=.001). There was no evidence of mediation through (lower) employee happiness (*indirect effect*=-.009, *SE*=.007; 95%*C.I.*=[-.026,.002]), which suggests that employee empathy is essential for handling customer disappointment; decreasing displayed happiness is not sufficient. The model shows a significant effect of the control variable (customer happiness at T-1) on customer happiness at T+1 (*B*=.258***, *SE*=.058; 95%*C.I.*=[.143,.373]), indicating that customers maintain a consistent level of displayed happiness in interactions. Beyond this effect, employee empathy was shown to increase customer happiness after prior disappointment.



Indirect effect through employee empathy = .042 (.015), 95% C.I. [.015,.074].
Indirect effect through employee happiness = -.009 (.007), 95% C.I. [-.026,.002].
N=475 employee messages, R^2 =.133. * $p < .05$, ** $p < .01$, *** $p < .001$.
Numbers in parentheses represent standard errors.
Customer happiness at T-1 is included as a control.

Figure 11.
Employee empathy mediates move from customer disappointment to customer happiness.

2.4.4.1.2 Interaction Level Analyses and Results

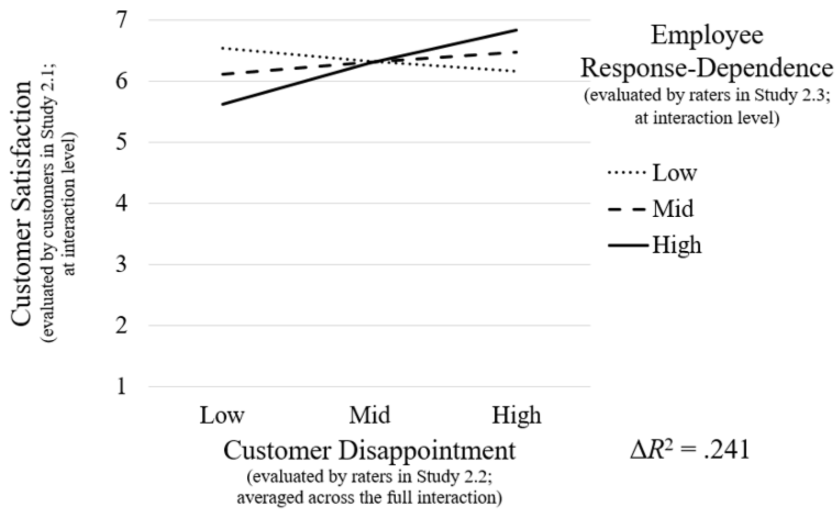
Hypothesis 11 was also supported: Employee response-dependence mitigated the negative effect of customer displays of disappointment on customer satisfaction. Customer disappointment (evaluated by raters in Study 2.2) was measured at the message level. To test interaction level effects, we averaged the disappointment scores of all customer messages in an interaction. Employee response-dependence (evaluated by raters in Study 2.3) and customer satisfaction (rated by customers themselves in Study 2.1) were measured at the interaction level. In all models, customer happiness (evaluated in Study 2.2, averaged across the full interaction) was entered as a control variable.

Model 5.1 in Table 10 shows that customer disappointment does not predict customer satisfaction (B=-.131, SE=.235, p=.577, R^2 = .097), when controlling for customer happiness. Model 5.2 reveals that employee response-dependence positively predicts customer satisfaction, beyond the effects of customer disappointment and happiness (B=.370, SE=.117, p=.002, ΔR^2=.101). Lastly, Model 5.3 tests and supports Hypothesis 11, showing that employee response-dependence moderates the negative effect of customer disappointment. We conducted bootstrap analyses with 5000 samples (SPSS Macro PROCESS, Model 1; Hayes, 2017), with customer disappointment as the IV, employee response-dependence as the moderator, customer satisfaction as the DV, and customer happiness as the control variable. The model confirms that employee response-dependence weakens the negative effect of customer disappointment (B=.820, SE=.141, p<.001, ΔR^2=.241) on customer satisfaction. Figure 12 depicts the conditional effects of customer disappointment at low, medium, and high values of employee response-dependence (16th, 50th, and 84th percentiles, respectively). With low employee response-dependence, customer disappointment negatively predicts customer satisfaction (B=-.781, SE=.213, p<.001). With moderate employee response-dependence, customer disappointment does not predict customer satisfaction (B=-.029, SE=.191, p=.879). With high employee response-dependence, customer disappointment positively predicts customer satisfaction (B=.586, SE=.233, p=.014).

Table 10.
Study 2.4 Customer discrete emotions and employee response-dependence predicting customer satisfaction

	Model 5.1				***Model 5.2***				***Model 5.3***			
	B	**SE**	**Lower CI**	**Upper CI**	**B**	**SE**	**Lower CI**	**Upper CI**	**B**	**SE**	**Lower CI**	**Upper CI**
Constant	5.853 *	0.462	4.933	6.773	4.018 ***	0.727	2.572	5.464	10.256 ***	1.168	7.479	12.128
Customer Averaged Disappointment[a]	-0.131	0.235	-0.598	0.336	-0.213	0.224	-0.659	0.233	-4.979 ***	0.801	-6.338	-3.148
Customer Averaged Happiness[a]	0.455 **	0.201	0.054	0.856	0.335	0.195	-0.052	0.723	0.282	0.164	-0.045	0.609
Employee Response-Dependence[b]					0.370 **	0.117	0.137	0.602	-0.664 *	0.203	-1.069	-0.260
Customer Averaged Disappointment[a] X Employee Response-Dependence[b]									0.820 ***	0.141	0.539	1.100
R-squared	0.097				0.198				0.438			
Δ R-squared					0.101**				0.241***			

Dependent variable: Customer Satisfaction (as evaluated by customers in Study 2.1).
N = 84 service interactions. * $p < .05$, ** $p < .01$, *** $p < .001$.
[a] as evaluated by raters in Study 2.2.
[b] as evaluated by raters in Study 2.3.



N=84 service interactions.
Customer happiness (evaluated by raters in Study 2.2; averaged across the full interaction) is included as a control.

Figure 12.
Employee response-dependence moderates the effects of customer disappointment on customer satisfaction.

2.4.4.2 Study 2.4 Summary

Study 2.4 extends our findings by examining the end goal of improving customer outcomes and showing that employee response-dependent affective behaviors improve subsequent customer affective displays and customer satisfaction after the service interaction ends. We show that employee empathy displays in response to customer disappointment leads to more customer displays of happiness. Additionally, employee response-dependence reactions to customer disappointment increase customer satisfaction. Together, the findings support our theory that employees' response-dependent displays improve customer affect, as well as customer service outcomes.

2.4.5. Study 2 Summary and discussion

Study 2 offers additional support of our first eight hypotheses regarding response-independence and dependence in employee affective behaviors. Our analyses of discrete emotions in employee and customer messages (Hypotheses 5 to 8) further support both response-independence and dependence patterns in employee affective displays. These analyses confirm the increased complexity of employees' emotional labor that we posit: Employees express happiness only when customers are happy and convey empathy when customers are disappointed. Ratings of employee and customer messages in simulated interactions at the interaction level also indicate that employees are more attentive to customers than vice versa; in other words, employee response-dependence is greater than customer response-dependence. Finally, Study 2 findings show that employee response-dependence improves service outcomes.

2.5. Discussion

We conceptualize service employees' work as a delicate balancing act of the varied complex requirements of emotional labor, including response-dependent regulation and attending to customer displays, rather than merely displaying good cheer consistently, as implied by previous research. In contrast, customers, who are in the more powerful position and are unconstrained by emotional labor, engage in response-independent regulation and solely attend to their own emotions. Thus, we add to the literature on intrapersonal and interpersonal effects of affective displays by demonstrating that partners in the same interaction vary in their regulation processes depending on their level of power within the interaction and emotional labor requirements. We also demonstrate that employee response-dependent affective behaviors improve customer outcomes, thus achieving the regulatory goal of employees.

Our results offer novel insights for theory, research, and practice. We contribute to theory on emotional labor by moving beyond assertions that service employees consistently display positive emotion and highlighting that employees have a more complex role, such that they must continuously monitor customers' affective displays and respond in kind. The requirement that employees adapt their displays to customers has received little attention in prior empirical research. Our findings confirm that employees tailor their displayed affect to each customer, thus exercising a more refined version of emotional labor. In addition to using surface or deep acting to regulate their own affect, employees also gauge appropriate affective displays for each customer. Determining the appropriate response to a frustrated or angry customer is not simple nor obvious, rather this step adds to the work of employees and we believe that it is deserving of further research and managerial attention within organizations. Beyond the emotional labor of managing one's affective displays (Grandey, 2000, 2003), the task of attending to the affective states of customers may require emotional intelligence (Ashkanasy & Daus, 2005), or what Azab, Clark and Jarvis (2018) label as "Positive Psychological Capacities."

Employees' attentive (response-dependent) displays are, at times, traditional emotional labor displays of good cheer. An employee can show recurring displays of positive affect (greeting, smiling, acting polite, and ending an interaction with the phrase "have a nice day") when appropriate. The challenge that we make salient across this set of studies is an employee's subsequent behavior when engaging with a customer who expresses discontent. An employee's positive affective display appears vacuous in this instance; rather, customer discontent calls for an apology by the employee or an expression of empathy – that is, appropriate response-dependent displays. Juggling between "automatic" positive display mode and "attentive" display mode is likely to be fatiguing.

Our final study shows that this complex work of service employees results in positive consequences for customers and service organizations. Employee adjustments to customer discontent lead to more positive customer displays and to higher customer satisfaction. These positive outcomes reinforce employees' use of response-dependent affective displays because they attain organizational goals. However, these positive outcomes disregard the possible negative consequences that service work requirements may have on the employees themselves. This trade-off between customer positive outcomes and employee well-being must be considered in further theory and in practice.

A second theoretical and methodological contribution that our studies offer is the focus on, and analyses of, individual messages in social interactions, which highlight the micro-foundations of social interactions (Hackman, 2003) and service-delivery institutions (Collins, 1981). For example, the finding that interpersonal adaption is stronger among employees than customers further supports the idea of customers as informal managers of service operations (Grandey et al., 2010), and of the social stratification between employees and customers, which Shamir (1980) described as a version of servility.

Practically, our results illustrate the challenges of service work and make salient the predicaments involved in customer service delivery. The low power position of service employees as compared to their customers, requires that employees navigate between using pleasantries and continuously adapting their affective displays for the purpose of pleasing customers; this complex responsibility offers a new vantage point for explaining the high burnout rates in this workforce segment. The sentiment analysis tool we apply to our data can be used for real-time monitoring of service employees' affective displays, which can preempt cases of customer post-service dissatisfaction and employee stress. Additionally, it can facilitate managerial interventions in service delivery, when needed (Bromuri et al., 2020).

2.5.1. Limitations and Directions for Future Research

Our study has some limitations. First, we analyze written interactions, which limits generalizability to other channels. For example, affective displays in vocal exchanges may be hard to control, automatic, and spontaneous, while people can choose what they present in text interactions (Derks et al., 2008). People can convey affect in chats, using capital letters and emoticons (Byron & Baldridge, 2005), but text interaction partners see fewer nonverbal displays (e.g., smiles or frowns). Thus, text may allow more regulation and more hiding or faking of affect. It is also possible that customers who seek service through text, lack the ability to attend to employee affective displays, whereas employee selection considers emotional abilities. Customers might also choose text communication because they believe it helps in regulating affective displays. These and similar questions call for future research. Notwithstanding, the significant effects we find in (the more restricted medium of) chat offers a conservative test of our theory, suggesting likely more substantial effects in in-person interactions.

Second, the sentiment analysis tool used in Study 1 generates objective affective scores (Yom-Tov et al., 2018). As such tools do not capture all instances of affective displays (Serrano-Guerrero et al., 2015), there are likely more affective displays than the tool (and thus our data) recognized; we believe this positions our results conservatively such that the effects we report are stronger in reality. Also, sentiment analysis decision rules must deal with human emotional complexity. Assigned values depend on developers' logic and on corpora labeling by humans. These tools are still being developed and may have errors and biases, so caution must be applied. To address this limitation, we conducted controlled studies with human judges rating the response-independence and response-dependence of employees and customers at the interaction level and their displays of discrete emotions at the message level. Still, we suggest further research to fully support our intuition and to develop more sensitive sentiment analysis tools.

Third, affective displays can obviously be more complex than those we examined. Negative displays can comprise discrete emotions such as anger, frustration, or sadness, and positive displays can comprise those such as happiness, delight, or gratitude. But without nonverbal cues, discerning discrete emotions at the message level with only a few words is complex for both automatic analysis tools and humans. Thus, we first examined a less nuanced view of the positive and negative affective displays in each message (Study 1). Although this was not our focus, we also examined a small set of discrete emotions using judges' ratings of employee and customer messages in a controlled study (Study 2). A more thorough examination is clearly needed. We hope future work will follow up with analyses at greater granularity. Finally, our analysis presumes causal effects due to the clear ordering of the messages. But order is not always indicative of causality

PAPER 3: CUSTOMER AND EMPLOYEE AFFECTIVE DISPLAYS AS EXPEDITIOUS PREDICTORS OF CUSTOMER SATISFACTION

3.1. Introduction

Customer evaluations of service interactions provide critical feedback about the extent to which a service organization meets the needs and expectations of its customers (Andreassen, 1999). Customer evaluations (and customer complaints) offer an opportunity to learn about what has been done well, and what about a service delivery system needs improvement (Groth & Grandey, 2012; McCollough et al., 2000). However, dissatisfied customers do not necessarily complain, which is why managers must actively work to identify levels of customer satisfaction (Andreassen, 1999). Service organizations invest extensive resources in follow-up customer satisfaction surveys; however, such surveys take considerable time to administer and analyze. Thus, current insights about customer satisfaction are available only after a significant amount of time has passed from when a service interaction occurred.

Based on the *affect-as-information approach* (Clore et al., 2001), we propose that an analysis of the affective cues displayed by customers can offer expeditious access to insights about customer satisfaction. We expect that customers rely on their affect when making satisfaction judgments; thus, we predict that customers' overall affective displays during an interaction can help predict their reports of satisfaction after the interaction. Moreover, in accordance with the *peak and end model*, we posit that when customers retrospectively evaluate a service, they not only consider the entire service interaction (Fredrickson & Kahneman, 1993), but they are also likely to rely on the most extreme and final elements of the interaction (Ariely & Carmon, 2000, 2003; Fredrickson & Kahneman, 1993). In this regard, we expect customers' peak (most extreme) and end (final) affective displays to add information about customer satisfaction beyond their overall affective displays.

With respect to our goal of enabling expeditious predictions of customer satisfaction, we conduct exploratory analyses on the affective cues of service employees, in addition to the affective cues of the customers. We expect a separate effect of service employee affective displays on customer evaluations because employees are integral to service interactions, and as such, we propose that their displays offer additional information for predicting customer evaluations. Lastly, in line with prior findings about individuals' greater reliance on affect in situations of uncertainty, we examine customer satisfaction in the particularly problematic case of outcome service failures. We suggest that customer and employee affective cues are more indicative of customer satisfaction when customers' issues are not resolved.

The key elements that we propose to drive customer satisfaction judgements are their own *affective displays* (i.e., the customer) and those of their interaction partner (i.e., the service employee; e.g., Dallimore et al., 2007; Staw et al., 2019). Affective displays are inherent in individual messages of customers and employees that compose service interactions; each message may convey what a person feels or thinks, or what they choose to display. Importantly, in contrast to the difficulty that organizations have in accessing the genuine feelings of customers and employees without the use of obtrusive and costly measures, people's displayed affect can be directly and easily observed. We therefore propose that affective displays can serve as an accessible source of information for assessing customer satisfaction.

In the current study, we apply a broad definition of "affective displays" to our exploratory examination of displayed affect in employee-customer service interactions; we compare the effects of overall affect displayed to snapshots of displays of affect in specific messages – namely, peak (highest) affect and end (final) affect – in predicting customer satisfaction. We propose that these affective displays are expeditious indicators of post-service satisfaction (Ariely & Carmon, 2000, 2003; Fredrickson & Kahneman, 1993). We focus on affective displays in text-based service interactions, an increasingly popular service medium in which all customer and employee expressions are written and are therefore relatively easily accessible; however, one downside to these data is that vocal feedback and facial nonverbal displays (e.g., Dallimore et al., 2007) are not available.

Our study contributes to both service research and service management. Research-wise, we highlight a highly granulated view of service interactions, which makes salient specific snapshots. First, we support the affect-as-information theory by showing the contribution of affective displays to customer reports of satisfaction. We demonstrate that affect contributes to the prediction of customer satisfaction to a much greater extent than objective, operational features such as employee response time and issue complexity. Second, we show that, other than the overall (mean) affective display, specific messages within service interactions are predictive of overall customer satisfaction. Third, we account for the complexity of dyadic service interactions and illustrate the unique effects of both partners' affective displays on determining customer evaluations. Fourth, we demonstrate that the information conveyed by affective displays is particularly useful in circumstances of customer uncertainty (i.e., an unresolved issue), and suggest that outcome service failures result in uncertainty. We test and confirm all these effects in written (rather than voice or face-to-face) service interactions. Management-wise, we reveal a shortcut option for gaining expeditious insight into customer satisfaction after a service interaction.

3.1.1. Affect-as-Information

The important role of affect in guiding judgments is repeatedly noted and recognized (Forgas, 1995). When people make judgments about a particular event, they implicitly ask themselves, “How do I feel about it?” (Schwarz & Clore, 1983), and subsequently use the answer to determine their evaluations. The affect-as-information approach thus suggests that affect is a source of information that people use in their everyday lives (Clore et al., 2001). Experiencing a sense of pleasantness, for instance, provides people with information about the value of the matter at hand, and thus prompts them to evaluate and interpret their overall environment as positive. When elicited feelings are positive, people are likely to perceive the context or situation as desirable, whereas if elicited feelings are negative, people are likely to perceive it as undesirable.

In the context of service delivery, the affect-as-information approach implies that there is a relationship between customer affect and customer service evaluations, a notion that is supported by some research (Bagozzi et al., 1999; Gardner, 1985); this association has even been demonstrated in short-lasting service interactions (Mattila & Enz, 2002). For example, Schoefer and Diamantopoulos (2008b) and Schoefer (2008) found that emotions of discontent negatively predict customer satisfaction, whereas pleasure emotions positively predict satisfaction, and Hennig-Thurau et al. (2006) showed that an increase in customer positive affect was related to higher levels of customer satisfaction. In a meta-analysis of 13 studies, which examined 72 correlations between affect and customer satisfaction (Szymanski & Henard, 2001), 67% of the correlations were found to be positive and significant, and an additional 20% were positive although not significant.

Considering the theoretical basis of the affect-as-information approach, one can presume that customers rely on their affect to make judgments about their satisfaction with service interactions. Thus, affective displays offer cues about felt affect, and an analysis of affective displays can offer predictive information about subsequent customer evaluations. As noted previously, affect and evaluations are empirically related, suggesting that the affective displays of customers can offer cues about their satisfaction (Fisher & Ashkanasy, 2000; Rafaeli et al., 2020; Yom-Tov et al., 2018). Specifically, customer displays of negative affect can be viewed as a cue of dissatisfaction, while displays of positive affect can be perceived as a cue of satisfaction (Diefendorff & Gosserand, 2003).

In the present study, we focus on individual messages comprising service interactions and measure affective displays on one dimension that ranges from very negative to very positive. If customers use their affect as information when making judgments of service interactions, we expect a positive relationship between their overall affective displays within an interaction and their evaluation of it after it ends. Specifically, we expect that higher overall customer affect (i.e., displays of more positive and less negative affect) within the interaction will be associated with higher satisfaction after the interaction.

Hypothesis 1. *The overall level of customer affective displays in a service interaction is positively related to customer satisfaction after the interaction.*

3.1.2. Peak and End Affective Displays

When individuals make judgments, they not only monitor the valence of their feelings toward the matter at hand, but also the intensity of these feelings. People implicitly (and typically unconsciously) ask themselves, “How strongly do I feel about it?.” Feelings that are more accessible, due to their intensity and salience, have a greater influence on judgments (Clore et al., 2001). Thus, recalled affect may not be fully captured by one's overall (mean) affect. An interesting question that emerges, therefore, regards how affect during different parts of an interaction relate to one's overall customer satisfaction evaluation. In other words, which elements of customers' affective displays predict subsequent customer satisfaction? Post-service evaluations of service delivery require customers to provide an overall evaluation, meaning that they must integrate the multiple messages of the interaction. However, research has shown that people do not consider all moments of an interaction because of people's reliance on shortcuts, which makes some parts of the experience more salient when determining an overall evaluation (Ariely & Carmon, 2003). Such summary evaluations are crucial because they influence people's decisions of whether to recommend a service and/or use it again.

Available analyses regarding how people summarize and evaluate experiences posit that overall evaluations are based on information that is most representative (Fredrickson & Kahneman, 1993; Kahneman, 2000). A representative moment, or a snapshot moment, is constructed and then used to evaluate an experience. A representative moment of an experience is determined by the most extreme (peak) affect experienced and the final (end) affect that is experienced. Such representative moments are argued to determine the global evaluation of an entire experience (Kahneman, 2000). We extend this theory to the service context, suggesting that peak and end customer affective displays within service interactions predict customers' subsequent evaluations of satisfaction.

Research has demonstrated the peak and end effect is present in different situations, both unpleasant and pleasant. For example, peak and end effect has been confirmed during unpleasant experiences, such as when completing an unpleasant task (Fredrickson & Kahneman, 1993), during medical procedures (Redelmeier et al., 2003), and when experiencing chronic symptoms

(Schneider et al., 2011); such findings have been demonstrated in both lab (e.g., Hoogerheide & Paas, 2012) and real-life settings (e.g., Schneider et al., 2011). To illustrate, among rheumatology patients who reported daily recall and momentary ratings of pain intensity over one month using an electronic diary, peak and end momentary pain ratings predicted daily summary pain ratings (Schneider et al., 2011). Additional research has demonstrated peak and end effect with regard to pleasurable experiences. For example, individuals rated a happy life that ended suddenly as better than one with additional years of only mild happiness (Diener et al., 2001). Moreover, the peak and end rule has been demonstrated in evaluations of material goods (Do et al., 2008) and in evaluations of vacations (Geng et al., 2013).

Peak and end effect has also been illustrated in regard to affect. In one study, Fredrickson and Kahneman (1993) asked participants to watch aversive film clips, rate their emotion whilst watching the clip– after having finished watching the clip – and provide a global evaluation; they reported that participants' most intense, real-time negative emotion predicted the global evaluations. In addition, Geng et al. (2013) asked participants to report on their level of happiness on each day of their vacation and to evaluate the overall vacation one day after it ended. The most extreme happiness rating (i.e., peak) and the final rating (i.e., end) predicted the overall evaluations. Similarly, Baumgartner, Sujan, and Padgett (1997) showed that the moment in which an advertisement elicits the most positive experience was recalled in consumer evaluations of the advertisement.

Importantly, however, these and similar studies on the peak and end effect have focused primarily on situations that involve either negative affective experiences or positive affective experiences. Yet, real life experiences, including service interactions, often comprise both positive and negative affective moments. We found only one study that tested and confirmed the peak and end effect in the context of real-life service delivery (Verhoef et al., 2004); however, this empirical study of 97 customers did not consider employee effects nor did it consider the relevance of outcome service failure on peak and end effect. Thus, our goal in the present study is to examine the contribution of peak (highest) and end (final) affective displays in predicting customer post-service satisfaction (see Figure 13 for an illustration of different possible peak and end displays *across 4 random interactions, all of which comprise exactly 10 messages*; this figure is included for illustration purposes only and does not reflect study results).

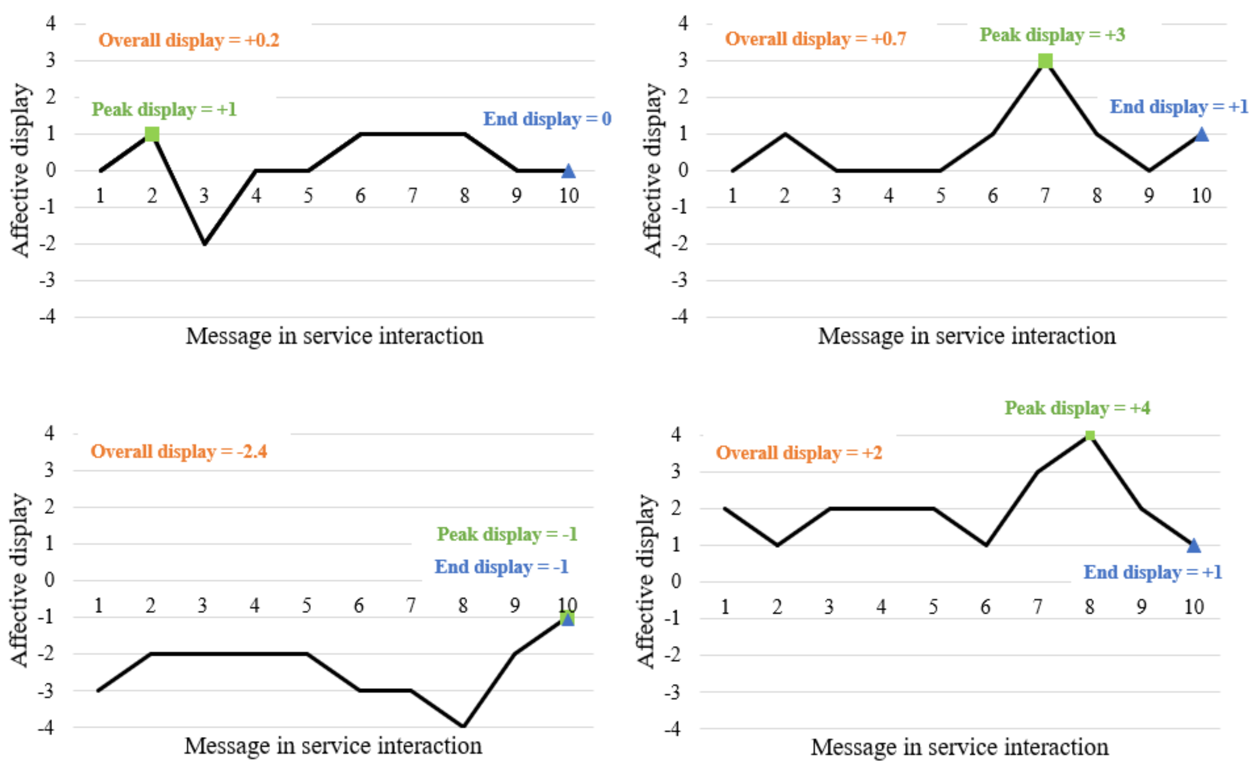


Figure 13.
Illustrations of four service interactions with different overall, peak, and end affective displays across 10 messages of an interaction.

We predict that these peak and end effect will be present in the data, above and beyond the effect of the overall displayed affect (Hypothesis 1). Moreover, since we use a unidimensional scale for measuring the affective display in each message, the peak and end displays, similar to the overall display, can be negative, neutral, or positive. We expect that higher peak and end displays will predict higher customer reports of satisfaction, above and beyond the basic effect of the overall display. For example, we expect that customers whose peak displayed affect is extremely positive will report higher levels of satisfaction as compared to customers whose peak displayed affect is lower, perhaps mildly positive, neutral or negative; we predict that a customer who writes, "*Thank you! You were extremely helpful*" – indicating a rather high peak display – is likely to report being more highly satisfied than a customer who writes, "*Thanks.*" In contrast, we expect that customers whose peak displays are negative, which would be indicative of something having gone wrong in the interaction, will be dissatisfied.

Hypothesis 2a. *The peak customer affective display in a service interaction is positively related to customer satisfaction after the interaction, beyond the effect of overall customer affective display.*

To complement the "peak" effect predicted in Hypothesis 2a, we also expect an effect of the "end" (or final) affective display. Hypothesis 2b suggests that the affective display in the final customer message predicts customers' overall post-service evaluations. We expect this end effect because service interactions reflect a goal-directed situation; in other words, customers contact service providers for a particular purpose. As Fredrickson (2000) noted, in goal-directed situations, an end effect is likely because the end symbolizes the outcome of one's objective. Customers who display positive affect in their final message to an employee are likely satisfied, whereas customers who end an interaction with displays of discontent (e.g., "I'm extremely disappointed with your service. Bye.") are likely dissatisfied. Thus, we propose that a higher or lower end display will lead to higher or lower reported satisfaction, respectively, after the service interaction ends. This prediction is additionally supported by the recency effect (Murdock, 1962); the end affective display is also the most recent and therefore most likely to be considered when a customer recalls a situation.

Hypothesis 2b. *The end customer affective display in a service interaction is positively related to customer satisfaction after the interaction, beyond the effect of overall customer affective display.*

3.1.3. Employee Affective Displays as Additional Information

Thus far, we have discussed intrapersonal effects on customer satisfaction, predicting connections between what customers display or feel during a service interaction and what they recall and report regarding their satisfaction with the interaction. A second source of information that we propose can help predict customer satisfaction ratings is employee affective displays during a service interaction.

Service employees are critical participants in frontline service. Employees and customers are defined as "co-creators" of service delivery (Grönroos & Voima, 2013) and employees are presumed to be the focal facilitators of the service "Moment of Truth" (Groth et al., 2019). The social nature of service interactions (Henkel et al., 2017), and the interdependence between employees and customers that is essential for progress and completion of service interactions (McCallum & Harrison, 1985), means that employee behaviors can influence customers. In particular, the interaction between customers and service employees is integral to customers' evaluations of service quality (Bitner et al., 1990; Gwinner et al., 1998; Parasuraman et al., 1985). We suggest that information about employees' affective behavior within an interaction can help predict customer satisfaction. We base this prediction on the known link between employee and customer affect and on the extensive line of research on emotional labor. Importantly, in Paper 2 of this dissertation, we did not formulate hypotheses on how employee affective displays influence customers. Here we do propose such an influence, suggesting that employee affective *displays* can be a source of information about customer satisfaction.

That employee affect influences customer affect is the foundation on which requirements that specify that service employees engage in *Emotional Labor* is based; service employees are thus required to display specific affect in their interactions with customers (Geddes & Callister, 2007; Grandey, 2000; Rafaeli & Sutton, 1987; Sutton & Rafaeli, 1988). The goal of these requirements is to manage the effects of employees on customers (Rafaeli & Sutton, 1987), and available research confirms these effects (e.g., Pugh, 2001; Zapf, 2002). Research specifically shows that service employees' affect influences customers' *felt* affect (Liu et al., 2019).

A number of studies on face-to-face service interactions have provided evidence for the relationship between service employees' affective displays and customer satisfaction. To illustrate, a study of fast-food chains in Singapore showed that cashiers' positive displays during an interaction (coded by research assistants) were positively related to customers' reported satisfaction (Tan et al., 2004). Similarly, two studies of sales clerks in retail shoe stores in Taiwan showed that research assistants' ratings of clerks' affective displays predicted customers' willingness to return to the store and to recommend it to friends, as reported upon leaving the store (Tsai, 2001; Tsai & Huang, 2002). A study of food/coffee service providers showed that overall employee smile scores (rated by coders) positively predicted customers' reported satisfaction (Barger & Grandey, 2006). Yet another study showed that coders' reports of bank tellers' displayed positive affect were positively related to customer evaluations of service quality (Pugh, 2001). Similarly, a study of ten service industries showed that employee affective displays, as measured by independent observers, positively predicted service encounter satisfaction, as reported by the customer (J. S. C. Lin & Lin, 2011).

The common assumption is that employee affect influences customer satisfaction through its influence on customer *felt* affect (Liu et al., 2019). However, customer felt affect is not necessarily *displayed* by customers. Customer affective displays, which is what organizations can assess, sometimes diverge from felt affect because people's may utilize emotion regulation strategies (Medler-Liraz & Yagil, 2013). Thus, assessments of customer affective displays are unlikely to capture the full range of customer felt affect. Various components of customers' felt affect in response to employees' affective displays are unlikely to be measurable with currently utilized tools that assess customer felt affect. Toward the goal of expeditious predictions of customer satisfaction, and to compensate for the lack of complete information on customer affect, we propose that employee affective displays can serve as an additional source of information for predicting customer satisfaction.

Our prediction is that the more positive an employee's affective displays, the more satisfaction the customer will report. Service employees cannot display negative affect such as anger or rudeness (Grandey & Diamond, 2010), but employees can vary the intensity of their affective displays; for example, they may apologize mildly ("Sorry to keep you waiting") or mightily ("I really apologize for your long wait"). Thus, we presume that there will be variations in the level of positivity of employee displays. In this regard, we predict that higher levels of employee affective displays will produce higher levels of customer post-service satisfaction.

Hypothesis 3a. *The overall level of employee affective displays in a service interaction is positively related to customer satisfaction after the interaction, beyond the effects of customer affective displays.*

Hypothesis 3a predicts an effect of overall employee affective displays on customer satisfaction, beyond the effects of customer affective displays. In addition to the effect of overall employee affective displays, we propose that specific employee affective displays within an interaction can convey information about subsequent customer satisfaction. Building on the idea of the peak and end effect described earlier, we presume that recall of specific moments within an interaction uniquely predict customer satisfaction, separately from the overall experience. Thus, we propose that peak and end affective displays *of the employee* will help predict customers' evaluation of the service, beyond the effect of the overall (mean) display. We expect extreme moments of employee affective behavior – the peak and end employee affective displays – to influence subsequent customer satisfaction in a fashion that complements the effects of customer peak and end displays. We base this proposition on the assumption that peak and end employee displays are likely to be salient in customers' experience, and thus influence their post-service ratings of satisfaction. Importantly, we do not suggest that employee displays replace the information provided by customers' own affect displays. Rather, we propose that recall of employee behavior provides additional information and increases the predictive power of affective displays on the customer's overall assessment of the interaction.

Hypothesis 3b. *The peak employee affective display in a service interaction is positively related to customer satisfaction after the interaction, beyond the effects of customer affective displays.*

Finally, we expect employees' end displays to also predict customers' evaluations of service interactions. A positive ending implies that the goal of the service interaction was achieved, and thus one can expect a positive evaluation (Fredrickson, 2000). More generally, an employee's higher end display can serve as a cue to the customer that the employee was helpful and constructive, which we expect will lead to more favorable customer satisfaction ratings. In contrast, a lower employee end display suggests that the interaction ended unsuccessfully. For example, an employee apology at the end of the interaction can be a reminder that something in the service interaction failed to meet customer's expectations.

Hypothesis 3c. *The end employee affective display in a service interaction is positively related to customer satisfaction after the interaction, beyond the effects of customer affective displays.*

3.1.4. The Boundary Condition to Effects of Affective Displays: The Case of Outcome Service Failures

The final component of our research identifies a boundary condition to the predictive power of affective displays on customer satisfaction. We propose that customer and employee affective cues are less relevant when customers receive what they want, and more indicative when customers experience uncertainty about the fulfilment of their needs. We base this proposition on previous findings, which indicate that affect is more informative in situations of uncertainty. Faraji-Rad and Pham (2017) found, for example, that consumers are more likely to rely on affect when making judgments in psychological states of uncertainty than in states of certainty. In a series of studies, Faraji-Rad and Pham (2017) demonstrated that priming uncertainty increases people's reliance on affect when making decisions and judgments. In their studies, uncertainty increased the effect of the pleasantness of a musical soundtrack on people's behavioral intentions regarding a product (e.g., number of books they want to buy over the next two months), and the effect of a product's visual appeal on a consumer's willingness to pay for it.

On the basis of the aforementioned studies, we suggest that affective displays will be more indicative of subsequent satisfaction in a situation of customer uncertainty following an outcome service failure. We presume that outcome service failure embodies uncertainty because it represents a failure in the service provided or a problem with the services rendered; in other words, this situation exemplifies a significant gap between what a customer expected and what was received (W. B. Lin, 2006). When customers attain their goals in a service interaction, they reach a sense of closure – they got what they wanted. In contrast, customers whose goals are not fulfilled in a service interaction, remain in a state of uncertainty; they remain unclear about whether or how their needs will be met. Thus, outcome service failure puts customers in a state of uncertainty. Building on the research of Faraji-Rad and Pham (2017), we expect that, in situations characterized by uncertainty, customers are more likely to rely on affective cues when evaluating their level of satisfaction. In contrast, when a service interaction is successful, customers have a clear picture of where they stand, and will not need additional (affective) cues to determine their level of satisfaction with a service interaction.

We suggest that customer satisfaction evaluations, first and foremost, reflect whether a service need was resolved. If needs are resolved, customers experience certainty about their situation and satisfaction is likely. In such cases, customers do not need other cues, and are therefore less likely to rely on affective displays when reporting on their satisfaction. When customer needs are not met in an interaction, however, customers experience less certainty about their situation, and thus, affective cues become an important source of information for satisfaction evaluations. In accordance with our reasoning about the specific moments that people use as sources of information, as presented previously, we offer the next two hypotheses:

Hypothesis 4a. *Following an outcome service failure, the positive relationship between the peak customer affective display in a service interaction and post-interaction customer satisfaction is stronger than when the customer issue is resolved.*

Hypothesis 4b. *Following an outcome service failure, the positive relationship between the end customer affective display in a service interaction and post-interaction customer satisfaction is stronger than when the customer issue is resolved.*

We also suggest that the affective displays of employees can provide additional useful insight into customers' evaluations of satisfaction, particularly when customers find themselves in a situation of uncertainty following an outcome service failure. As before, we base our prediction on the assumption that customers are satisfied when there is no outcome failure (i.e., they got what they wanted), but find themselves in a state of uncertainty in the case of an outcome failure. As noted previously, customer affect is less likely to be used as a cue for satisfaction after a customer issue was resolved because customer satisfaction is likely to already be high. As such, we hypothesize that employees' displayed affect is more likely to be considered in satisfaction ratings when customers are in a state of uncertainty (as a result of a service outcome failure) as compared to when customers experience certainty. Hence, our final hypotheses are:

Hypothesis 4c. *Following an outcome service failure, the positive relationship between the peak employee affective display in a service interaction and post-interaction customer satisfaction is stronger than when the customer issue is resolved.*

Hypothesis 4d. *Following an outcome service failure, the positive relationship between the end employee affective display in a service interaction and post-interaction customer satisfaction is stronger than when the customer issue is resolved.*

3.2. The Current Research

We tested our hypotheses using data on genuine frontline, text-based service interactions conducted online. Service interactions conducted in writing offer an excellent platform for testing our predictions because we can access the texts of customers and employees, analyze the affective displays in them, and connect these assessments to customer responses in post-service surveys regarding satisfaction and outcome service failure.

3.3. Method

3.3.1. Context and Data

We obtained and analyzed a large-scale dataset of 23,645 text-based service interactions of an airline company. These service interactions were mediated by LivePerson Inc. (http://www.liveperson.com/). The 23,645 text interactions included 146,091 customer messages and 155,189 employee messages sent between March 2016 and April 2017. Employee-customer interactions ranged from as few as two messages to as many as several hundred messages. The mean number of customer messages in an interaction was 6.18 (*SD* = 3.701), and the mean number of employee messages was 6.59 (*SD* = 3.659).

3.3.2. Variables

Table 11 offers a brief summary of the study variables and their operational definitions.

Affective displays. We assessed the affective displays in each message using an automated sentiment analysis tool called SentiStrength (http://sentistrength.wlv.ac.uk/), which was discussed in Paper 1. Scores represent the intensity of either the positive or negative affective display in each message. To test our hypotheses, we used the affective display score of each message to identify three values – overall, peak and end – for the customer and the employee in each interaction (see Table 11):

(1) ***Customer (Employee) overall display*** was defined as the mean of all affective display scores of the messages written by the customer (employee) in the interaction.

(2) ***Customer (Employee) peak display*** was defined as the highest affective display score of the messages written by the customer (employee) in the interaction.

(3) ***Customer (Employee) end display*** was defined as the affective display score of the final message written by the customer (employee) in the interaction.

Customer satisfaction **(CSAT)** was measured with a one-item, post-service question posed to customers immediately after the service interaction ended: "*How satisfied were you with the service from our advisor?*" (1="*Very unsatisfied*" to 5="*Very satisfied*").

Outcome service failure (hereafter, *Outcome failure*) was measured with a one-item question posed to customers immediately after the service interaction ended: "*Was your service need resolved in this interaction?*" (0="*yes*", 1="*no*").

Operational Variables

To examine the unique contribution of affective displays, our analysis controlled for multiple variables, which may influence customer satisfaction. Specifically, we controlled for employee response time because it can be an indicator of responsiveness and to affect the time that customers must wait to receive support (Maister, 1984; Yom-Tov et al., 2017). We also controlled for the length of the text (number of words) of customer and employee messages and the length of the interaction (number of turns), which reflect the issue's complexity and the effort it requires to solve (see Altman et al., 2020). Therefore, for each interaction, we also calculated the following variables:

(1) ***Employee mean response time (RT)*** was defined as the mean time that elapsed between an employee message and the previous customer message.

(2) ***Customer (Employee) mean number of words*** was defined as the mean number of words of all the messages a customer (employee) sent in an interaction.

(3) ***Number of turns*** was defined as the total number of turns that the customer and employee had in an interaction. A turn is defined as one iteration that includes a customer message followed by an employee response or vice versa.

3.4. Results

Table 12 reports the means, standard deviations, correlations, and collinearity statistics of all the study variables, and verifies that there is no multicollinearity between the independent variables (all variance inflation factor values are less than 5). Table 13 presents five ordinary least squares regression models, which we used to test our hypotheses. All the models were tested with the full sample of employee-customer interactions (*N* = 23,645). Model 1 includes only the control variables. Model 2 adds the customer overall affective display score (testing Hypothesis 1), Model 3 adds the customer peak and end affective display scores (testing Hypotheses 2a and 2b), Model 4 adds employee affective display scores (testing Hypotheses 3a-3c), and Model 5 adds the moderation effects of outcome service failure (testing Hypotheses 4a-4d). Table 14 depicts the practical implications of the results presented in Table 13; more specifically, it displays the percent change in the dependent variable (CSAT) for every 1-point increase in each predictor variable.

Table 11.
Description and operational definitions of study variables

Variable	Description of variable
Customer satisfaction (CSAT)	Customer response to the question: "How satisfied were you with the service from our advisor?" on a scale of 1 (Very unsatisfied) to 5 (Very satisfied)
Outcome failure	Customer "Yes" (0)/ "No" (1) response to the question: "Was your service need resolved in this interaction?"
Affective displays	
Cust (Emp) overall display	The mean of all affective display scores of the messages written by the customer (employee) in the interaction
Cust (Emp) peak display	The highest (maximum) affective display score of the messages written by the customer (employee) in the interaction
Cust (Emp) end display	The last affective display score of the messages written by the customer (employee) in the interaction
Operational variables	
Emp mean response time (RT)	The mean time that elapsed between an employee message and the previous customer message
Cust (Emp) mean number of words	The mean of the number of words of all the messages a customer (employee) wrote in an interaction
Number of turns	The number of turns that the customer and employee had in an interaction. A turn is defined as an iteration between a customer message and an employee message or vice versa

Table 12.
Means, standard deviations, Pearson correlations, and collinearity statistics of study variables

Variable	Mean	Standard Deviation	1	2	3	4	5	6	7	8	9	10	Tolerance	VIF
1. Emp mean response time (RT)	49.405	33.438	-										0.901	1.109
2. Cust mean number of words	13.824	8.920	.197**	-									0.912	1.096
3 Emp mean number of words	26.734	9.640	.191**	.176**	-								0.886	1.128
4. Number of turns	6.136	3.704	-.095**	-.181**	-.215**	-							0.647	1.546
5. Cust overall display	0.431	0.418	-.086**	.038**	.049**	-.129**	-						0.487	2.055
6. Cust peak display	1.357	0.744	-.096**	.019**	-.018**	.235**	.631**	-					0.438	2.282
7. Cust end display	0.935	0.816	-.040**	.020**	.020**	0.002	.534**	.576**	-				0.626	1.597
8. Emp overall display	0.867	0.589	-.072**	-.015*	.133**	-.194**	.203**	.075**	.082**	-			0.509	1.964
9. Emp peak display	2.119	0.820	-.124**	-.075**	.070**	.229**	.093**	.190**	.084**	.581**	-		0.470	2.127
10. Emp end display	1.423	1.208	-.163**	-.040**	.056**	.105**	.133**	.169**	.114**	.493**	.578**	-	0.614	1.630
11. CSAT (Customer satisfaction)	4.589	0.862	-.134**	-.077**	-.042**	.062**	.251**	.280**	.231**	.209**	.189**	.245**	-	-

N = 23,645 service interactions.

** $p < .01$.

Model 1 includes all our control variables and demonstrates that the total contribution of the four control variables is relatively modest [$R^2 = 0.022$]. Model 2 supports Hypothesis 1, which predicted that the overall customer affective display score would positively predict customer satisfaction [$\Delta R^2 = 0.063$, $F(1, 23558) = 1619.390$, $p < 0.001$]. The overall customer display positively predicts customer satisfaction ($B = 0.524$, $SE = 0.013$, $p < 0.001$), beyond the effects of the control variables. The results show that a 1-point increase in overall customer affective display increases customer satisfaction by 11.4%, which is 61% of the CSAT standard deviation (SD, see Table 14). Further, results demonstrate that the contribution of the overall affective display to customer satisfaction is three times larger than the contribution of the four operational variables combined (employee response time, number of words in customer messages, number of words in employee messages, and number of turns).

Model 3 supports Hypotheses 2a and 2b. It confirms that peak and end customer affective display scores positively predict customer satisfaction beyond the effect of customer overall display [$\Delta R^2 = 0.022$, $F(2, 23556) = 285.315$, $p < 0.001$]. Supporting Hypothesis 2a, peak customer display positively predicts customer satisfaction ($B = 0.170$, $SE = 0.011$, $p < 0.001$). The results of Model 3 illustrate that a 1-point increase in the peak customer affective display increases customer satisfaction by 3.7%, which is 20% of the CSAT standard deviation (SD, see Table 14). Additionally, in support of Hypothesis 2b, end customer display positively predicts customer satisfaction ($B = 0.090$, $SE = 0.008$, $p < 0.001$) and a 1-point increase in the end customer affective display increases customer satisfaction by 2.0%, which is 10% of the CSAT SD (see Table 14). These results indicate that higher overall, peak, and end customer affective displays lead to higher levels of customer satisfaction. Moreover, the results suggest that customer peak and end affective displays offer additional information for predicting customers' overall evaluations of satisfaction, beyond what is conveyed by the overall displayed affect.

Model 4 in Table 13 adds the employee affective variables as additional predictors of customer satisfaction [$\Delta R^2 = 0.043$, $F(3, 23553) = 397.043$, $p < 0.001$]. Results partially support Hypotheses 3a-3c, which stated that the overall, peak, and end affective display scores of employees would positively predict customer satisfaction above and beyond the effects of customer affective scores. Employee overall and end, but not peak, affective display scores are positive and significant predictors of customer satisfaction, and their addition to the equation does not change the effects of customer affective scores found in Models 2 and 3.

In support of Hypothesis 3a, overall employee display positively predicts customer satisfaction ($B = 0.175$, $SE = 0.012$, $p < 0.001$). A 1-point increase in the overall employee affective display increases customer satisfaction by 3.8%, which is 20% of CSAT SD (see Table 14). However, Hypothesis 3b, which predicted that peak employee display would predict customer satisfaction ($B = -0.015$, $SE = 0.009$, $p = .106$), was not supported. Yet, Model 4 did support Hypothesis 3c, which predicted that employee end display would positively predict customer satisfaction ($B = 0.099$, $SE = 0.005$, $p < 0.001$). A 1-point increase in the end customer affective display increases customer satisfaction by 2.1%, which is 11% of CSAT SD (see Table 14). In summary, higher employee overall and end affective displays lead to higher levels of customer satisfaction, but no such effect is found for peak employee display. More broadly, the analyses largely support our prediction that the affective displays of employees can offer information about subsequent customer satisfaction, beyond the information provided solely by the customer affective displays.

Finally, Model 5 in Table 13 tests our predictions regarding the boundary conditions of the previous predictions regarding the effects of affective displays on customer satisfaction. Our predictions in Hypotheses 4a to 4d were that outcome failure would moderate the effects of affective displays on customer satisfaction. Model 5 shows that adding outcome failure significantly improves the model fit [$\Delta R^2 = 0.328$, $F(5, 23548) = 2{,}951.463$, $p < 0.001$]. Not surprisingly, outcome failure has a large negative main effect on customer satisfaction (B = -2.171, SE = 0.031, $p < 0.001$). Consistent with previous findings on the association between outcome service failure to customer dissatisfaction (e.g., Smith et al., 1999), the satisfaction scores of customers who experienced outcome service failure are 2.171 points lower than those of customers who did not experience an outcome failure.

Hypotheses 4a to 4d, which stated that the effects of customer and employee affective displays in predicting customer satisfaction would be stronger following outcome failures, are also supported by Model 5[4] (Table 13); all of the interaction terms between affective displays and outcome failure are significant. Specifically, Model 5 shows that peak and end customer affective displays have larger positive effects on customer satisfaction in the outcome failure group (B = 0.276, SE = 0.020, $p < 0.001$ and B = 0.239, SE = 0.017, $p < 0.001$, respectively). In the event of an outcome failure, a 1-point increase in the peak and end customer affective display increases customer satisfaction by 7.4% and 5.1%, respectively (which represents 39% and 27% of the CSAT SD, respectively; see Table 14).

[4] We do not report the interaction between outcome failure and customer and employee overall affect in this model because multicollinearity between these terms and other variables in the model would render such a model invalid. We did test a model that included these two interactions as predictors instead of the interaction terms, in addition to the customer and employee peak and end display scores, which resulted in a significantly lower explained variance than that reported in Model 5.

With regard to employee affective displays, results are consistent with those of customer affective displays. The effects of employee peak and end displays are stronger in the outcome failure group, as we predicted (B = 0.079, SE = 0.015, p < 0.001, and B = 0.179, SE = 0.011, p < 0.001, respectively). A 1-point increase in the peak or end employee affective display, when an outcome failure occurs, increases customer satisfaction by 1.7% and 4.2%, respectively (which represents 9% and 22% of the CSAT SD, respectively; see Table 14). Thus, our results show significant positive effects of customer and employee affective displays on customer satisfaction, supporting our theory that customer satisfaction ratings can be predicted by customer and employee affective cues.

Finally, to compare the effects of the different affective display variables, we include the standardized coefficients (β) of customer and employee affective display variables in Table 13. In Model 5, we see that outcome failure has the largest effect, and that customer peak and end displays also have substantial effects on customer satisfaction in the case of outcome failure. Furthermore, we see that the affective displays of the employee (specifically, the employee's end display) also contribute to the prediction of customer satisfaction. Thus, assessments of both customer and employee affective information during a service interaction provide a substantial benefit for predicting post-service customer satisfaction.

Table 13.

Ordinary least squares regressions predicting customer satisfaction (CSAT) in interactions with and without outcome failure

	Model 1			Model 2			Model 3			Model 4			Model 5		
	B	**SE**	**β**	**B**	**SE**	**β**	**B**	**SE**	**β**	**B**	**SE**	**β**	**B**	**SE**	**β**
Constant	4.761 ***	0.023		4.476 ***	0.023		4.378 ***	0.023		4.162 ***	0.025		4.615 ***	0.020	
Operational variables															
Emp mean RT	-0.003 ***	0.000	-0.122	-0.002 ***	0.000	-0.053	-0.002 ***	0.000	-0.093	-0.002 ***	0.000	-0.063	-0.001 ***	0.000	-0.032
Cust mean # of words	-0.004 ***	0.001	-0.045	-0.005 ***	0.001	-0.053	-0.006 ***	0.001	-0.062	-0.005 ***	0.001	-0.054	0.000	0.000	0.001
Emp mean # of words	0.000	0.001	-0.003	-0.001	0.001	-0.053	-0.001	0.001	-0.013	-0.004 ***	0.001	-0.039	0.001 *	0.000	0.010
Number of turns	0.009 ***	0.002	0.037	0.017 ***	0.002	-0.053	0.004 **	0.002	0.019	0.006 ***	0.002	0.028	0.005 ***	0.001	0.023
Customer affective displays															
Cust overall display (H1)				0.524 ***	0.013	0.255	0.229 ***	0.018	0.111	0.167 ***	0.018	0.081	0.045 **	0.014	0.022
Cust peak display (H2A)							0.170 ***	0.011	0.146	0.158 ***	0.011	0.136	0.062 ***	0.009	0.053
Cust end display (H2A)							0.090 ***	0.008	0.086	0.089 ***	0.008	0.085	-0.007	0.007	-0.007
Employee affective displays															
Emp overall display (H3A)										0.175 ***	0.012	0.120	0.056 ***	0.010	0.039
Emp peak display (H3B)										-0.015	0.009	-0.014	0.001	0.008	0.001
Emp end display (H3C)										0.099 ***	0.005	0.139	0.014 **	0.005	0.019
Effects of affective displays in the case of outcome failure															
Outcome failure													-2.171 ***	0.031	-0.882
Cust peak display X Outcome failure													0.276 ***	0.020	0.135
Cust end display X Outcome failure													0.239 ***	0.017	0.102
Emp peak display X Outcome failure													0.079 ***	0.015	0.067
Emp end display X Outcome failure													0.179 ***	0.011	0.118
Adjusted R-squared	0.022			0.085			0.106			0.149			0.477		

Dependent variable : Customer satisfaction (CSAT)

B is the non-standardized regression coefficient; SE is the Standard Error; β is the standardized regression coefficient.

N = 23,645 service interactions. *** p < .001, ** p < .01, * p < .05

Table 14.
Practical effects of affective displays on customer satisfaction

	B	% Effect in terms of CSAT absolute value[c]	% Effect in terms of CSAT SD[d]
Effects of affective displays[a]			
Cust overall display	0.524	11.4%	61%
Cust peak display	0.170	3.7%	20%
Cust end display	0.090	2.0%	10%
Emp overall display	0.175	3.8%	20%
Emp peak display	-0.015	-[e]	-[e]
Emp end display	0.099	2.1%	11%
Outcome failure	-2.171	-47.3%	-252%
Effects of affective displays in cases of outcome failure[b]			
Cust peak display in cases of outcome failure	0.339	7.4%	39%
Cust end display in cases of outcome failure	0.232	5.1%	27%
Emp peak display in cases of outcome failure	0.080	1.7%	9%
Emp end display in cases of outcome failure	0.192	4.2%	22%

[a] These values (main effects) are taken directly from Table 13.

[b] These values (interaction effects) represent the sum of the B of the main effect of the respective affective display and the B of the interaction between the respective affective display and outcome failure variable, as displayed in Table 13.

[c] This column reports the percent change in CSAT with a 1-point change in the respective variable. It is computed by dividing each B value by the CSAT mean (4.589).

[d] This column reports the change in CSAT with a 1-point change in the respective variable in terms of % of CSAT SD. It is computed by dividing each B value by the CSAT SD (0.862).

[e] This computation is not included because the B coefficient is not significant.

3.5. Discussion

Our study contributes to theory and research on affect in customer service interactions. Our results highlight the unique ability of both interaction partners' affective displays to predict customer evaluations of satisfaction. In addition, our results indicate that the contribution of affective displays to customer satisfaction is larger and more substantial than that of operational information (e.g., employee response time). Our work strengthens the limited research on service interactions by showing that customers' overall, peak, and end affective displays positively predict their subsequent evaluations of service in a large-scale dataset of real-life customer behavior. We further add to the literature by demonstrating that effects previously shown with customers occur with employee affective displays as well; employees' overall, peak, and end affective displays are uniquely and positively associated with customers' post-service evaluations. Finally, we show that affective displays are more informative in cases of outcome service failures, suggesting that outcome failures cause uncertainty for customers. Overall, our findings offer powerful support for the important role of affect in satisfaction evaluations. Using a large-scale dataset of real employee-customer interactions, we show that assessments of affective displays can be a utilized as a managerial tool for preempting prolonged post-service customer dissatisfaction.

3.5.1. Research Implications

Our work offers implications to both frontline service research and to general research on affective displays. First, our findings support the idea of *affect-as-information* (Clore et al., 2001) and extend it to the field of frontline service, by showing that assessments of affective cues displayed by customers can predict customer satisfaction. We show that greater overall positive affective displays predict more favorable customer evaluations of service interactions, showing that the contribution of customers' overall affective display to customer satisfaction is three times larger than the joint contribution of operational features (e.g., employee response time and problem complexity). Thus, research on customer satisfaction might benefit from shifting focus from operations and employee behavior to assessing affective displays.

Second, our findings support the *peak and end effect* model (Fredrickson & Kahneman, 1993), identifying specific snapshots from interactions – the peak (i.e., most extreme, highest) and the end (i.e., final) affective displays – that are particularly predictive of customer evaluations. Application of the peak and end effect model to research of customer satisfaction might place more emphasis on the most extreme and final elements of the interaction.

Third, our exploratory analyses provide insight into the importance of considering affective displays of *both* partners in a service interaction. Employees are co-creators of service and are integral participants in service interactions (Grönroos & Voima, 2013). Employee affective displays, which are inevitably present in service interactions, can therefore offer information for research on customer satisfaction. Assessments of customer affective displays are unlikely to capture the full range of customer felt affect, because self-report measures and the automated assessments that we used are limited in their ability to identify customers' displayed affect (Heitmann et al., 2020). Employee affective displays can compensate for some of the limitations of the available assessments for customer affect, and thus, can contribute to expeditious predictions of customer satisfaction. Employee affective displays likely influence customer satisfaction through their effects on customer affect (Liu et al., 2019), but also uniquely predict customer satisfaction, beyond the predictive power of customer affective displays.

By showing the effects of the affective displays of employees as well as of customers, we confirm within-person effects (i.e., the effects of a customer's displays on his or her own satisfaction) previously implied by the peak and end model, but also show effects of affective displays of a person's interaction *partner* on a focal person's post-interaction evaluation. Previous research on the peak and end model referred only to within-person (intrapersonal) effects. We found only one study that examined *interpersonal* effects of peak displays; this study used facial expression analysis to evaluate peak affective displays in video-recorded entrepreneurial pitches, and found that peak displayed joy influenced the amount of funding that was pledged to the entrepreneurs (Jiang et al., 2019). The context of frontline service is very different than that of entrepreneurial pitches; thus, we contribute novel insights to research on the peak and end model by connecting it to service delivery and by considering dyadic effects, specifically the influence of one person's displays (a service employee) on a second person's (a customer) evaluations.

Previous research that argued that employee displays of affect <u>can</u> predict customer satisfaction (e.g., Barger & Grandey, 2006; J. S. C. Lin & Lin, 2011; Pugh, 2001; Tan et al., 2004; Tsai, 2001; Tsai & Huang, 2002) examined one-time or aggregated measures of employees' affective displays. We add to this research by examining the effects of nuances of displays *within a service interaction*, demonstrating separate and distinct effects of overall, peak and end affective displays, adding the "texture" *of employee displays within an interaction* as useful for predicting customer satisfaction *after* a service interaction ends. This addition also refines prevailing theory about emotional display requirements of service employees. Current research emphasizes employees' general affective displays during service delivery (Grandey, 2003, 2015; Rafaeli & Sutton, 1987), while we highlight the unique role of *specific* employee displays within an interaction.

Lastly, we offer a connection between affective displays and outcome service failure and argue that outcome service failures create uncertainty for customers. An outcome failure implies that a customer's issue was not resolved, and thus the customer cannot know with certainty that his or her needs or request will be met. That affective displays significantly predict customer satisfaction, *particularly when customers have encountered an outcome service failure* supports the idea that uncertainty results from outcome service failure. This adds to available research suggesting that psychological states of uncertainty increase people's reliance on affective inputs when making judgments (Faraji-Rad & Pham, 2017). We demonstrated that when there is certainty about an issue being resolved, customers are less likely to rely on affective inputs in making their post-service satisfaction evaluations.

3.5.2. Methodological Contributions

Our research demonstrates the utility and versatility of novel tools for studying affective features of service interactions (Rafaeli et al., 2017), namely automated sentiment analysis. With a few rare exceptions (e.g., Baier et al., 2020; Verhoef et al., 2004), the available research on affective displays in service relies primarily on self-report or observations, and on one-time measures or an aggregation of affective scores. Our method embraces the dynamic nature of service interactions and identifies specific points within an interaction that predict customer evaluations. Traditional self-report tools cannot monitor variations in customer and employee affect during a service interaction because this would necessitate interrupting the interaction, which would create measurement issues and potential priming effects. The technology of sentiment analysis (Serrano-Guerrero et al., 2015) offers a more fine-grained analysis of affective dynamics, and allows for an analysis of a large-scale dataset without being overly labor-intensive, time-consuming, and costly. In the current study, we were able to analyze over

20,000 service interactions and to measure customer and employee affective displays in over 277,000 messages; this wide spectrum of interactions enabled us to acquire a refined picture of text-based service delivery.

Moreover, our study demonstrates the utility of examining online service interaction data (such as our analysis of displayed affect) in the context of outcome service failure for predicting customer satisfaction. These data are typically collected as part of organizations' standard service processes, and they enable relatively simple and non-obtrusive access to natural customer behavior, as well as offer opportunities to expeditiously predict customer satisfaction. We note that relying only on statistical significance to make conclusions from analyses of a large dataset warrants great caution. To demonstrate the practical significance of study findings using such methods, we encourage additional computations such as the ones we include in Table 14, in which we report the percent change in the dependent variable following changes in the independent variables.

The novel contributions of the current research can extend to avenues for future research that are quite distinct from what we have examined in this paper. For example, the data and tools that we used can be applied to studies of emotional contagion effects, a topic that was beyond the scope of this paper. Based on both the novel methodological contributions of the current research, we offer some questions for future research: Do the peak affective displays of one interaction partner influence the other interaction partner's affective displays in the subsequent message? Another, broader question to ask might be: What is the potential influence of the affective displays of one partner to an interaction (e.g., a customer or a subordinate) on the affective displays of another partner (e.g., an employee or a manager)? Overall, we believe that with the use of these novel data and tools, there will be extensive opportunities for fascinating future research.

3.5.3. Managerial Implications

Our study highlights the importance for organizations to consider the affective displays of both customers and employees during service interactions. Our findings suggests that, through assessments of customer and employee affective displays, service managers can obtain swift insights about the quality of service interactions in their organization. Current practices geared toward gaining insight about customer satisfaction take considerable time to carry out. Our findings offer a way to obtain insight immediately after an interaction ends.

Although we examined archival data, the analysis method we used – automated sentiment analysis – can be implemented by organizations in real-time, and thus can offer insight into the overall, peak and end affective displays as interactions occur and upon their completion. Currently, service managers primarily monitor the speed of employee responses and the time it takes to complete an interaction; these two factors represent operational features of a service interaction. In contrast, we show that assessments of *specific* affective displays *within an interaction* are better predictors of customer satisfaction than operational features, especially in the important case of outcome service failure. Our methods offer managers a way to obtain estimates of customer satisfaction immediately upon completion of an interaction, thus saving them precious time. These data would enable managers to identify unsatisfied customers who may not necessarily complain, and to react swiftly to avoid continued or escalated dissatisfaction. These monitoring procedures can also enrich the type of feedback and training provided to employees.

Monitoring affective displays may prevent service failure, so long as managers take preventive action upon identifying low levels of satisfaction among customers. Ideally, employees would monitor the affective displays of customers throughout the entire interaction, while also working to address customer needs and provide efficient service. However, frontline service work is complex, and employees can easily overlook the task of affective display monitoring given the pressures put on them to deliver quick service. Our results suggest that customers rely on affective cues to a larger extent than employee response time. Thus, managers should encourage employees to invest more time and effort in monitoring their own and their customers' affective displays, even at the cost of slightly slower response times.

Therefore, another implication of our study regards employee training and goals; we suggest that the focus be amended such that employees are trained to pay close attention to customers' affective displays, especially during the particular points that we have shown are likely to be recalled when evaluating the service received – the peak (highest) and end (final) displayed affect, as well as the overall affect displayed. Managers might consider adding tools aimed toward developing service employees' emotional competences, which can help employees improve their abilities in monitoring their own and their customers' affective displays.

More broadly, because our study suggests that customers rely more on affective cues to evaluate service when experiencing an outcome failure than when their issues are resolved, organizations may consider relaxing their emotional labor requirements for employees. Rather than requiring employees to generally display positive affect, it may be more effective for them to display positive affect when issues cannot be resolved, thus increasing the likelihood of a positive customer experience even when a solution to the customer's problem is not available.

3.5.4. Limitations and Toward Future Research

Naturally, there are several limitations to our study. Our evaluation of affective displays in text-based interactions enabled us to analyze only customers' *observed* affect and not their internal affective states. Customers may regulate their displays to maintain a specific impression, something our analysis could not discern. It was not possible nor reasonable to contact the customers in our dataset to ask about their actual affect both because the firm did not allow it, and because contacting over 20,000 customers would consume tremendous resources. However, we believe that this is a minor limitation, especially given that some of our analyses replicate self-report findings from previous research.

Second, the complexity of customers' issues and/or their previous experiences with the company – which we could not code in the data that we received – might have also affected their evaluations. To partially overcome this limitation, we controlled for measures that might account for issue complexity, including the length of customers' and employees' messages and the number of turns required to complete an interaction. However, even if we had access to the content of customer messages, the large amount of data in our study limits our ability to manually code the topics that were raised in the interactions. We hope that future research will advance the use of automated methods, such as text analysis (Banks et al., 2018; Short et al., 2018), to unveil the full spectrum of information available in customer service interactions.

Notwithstanding these limitations, our findings highlight that customer recollections of service interactions represent the integration of salient and final moments of interactions into an overall evaluation of customer satisfaction. An open question remains as to whether these effects may somehow interact to mitigate or strengthen our observed effects. For example, our findings suggest that an extremely positive ending by the employee is likely to elevate subsequent satisfaction; but we cannot tell whether it might make an employee's overall pleasant affect redundant. Similarly, a very negative moment within an interaction might lead customers to ignore all other, more positive, moments. We could not find sufficient literature to formulate hypotheses regarding such relative or interactive effects of the peak and end. We are hopeful that our methods and findings will inspire future research that will disentangle this complexity.

GENERAL DISCUSSION

This dissertation advances the theoretical and practical understanding of affect in interpersonal exchanges at work, through a specific focus on interactions between employees and customers. Through examining individual messages as the unit of analysis, we offer insights about affective displays of partners in the same service interaction. Our methods illustrate that full texts of authentic service (or other social) interactions can be analyzed. Our archival data, which represents real service interactions, brings Organizational Behavior research closer to the field. It makes salient the value of text-based interactions, which received limited research attention, as a useful venue since text is easier to analyze than voice. Also, deconstructing service interactions into a sequence of messages enables exciting new research.

More broadly, our analyses demonstrate a novel approach for in-situ Organizational Behavior research, suggesting that the use of "digital traces" is a valuable data source for organizational research on affect (Rafaeli et al., 2019). Records and archives of messages are retained in multiple platforms; this work shows that affective behaviors can be gleaned automatically from such data using special software. These methods overcome costs and limitations of observer-based data collection, same-source bias issues, and self-report methods. Practically, our results illustrate the challenges of service work and make salient the complexities involved in customer service delivery.

We see real merit in our focus on real-life service interactions. Of course, experimental research replicating and confirming the causal effects we propose is essential. Nonetheless, we hope our work here will inspire others to examine these and other fascinating research questions.

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לניבוי דיווח שביעות הרצון, מעבר לממוצע ההבעות. עוד נמצא כי ההבעות הרגשיות של העובדים, השותפים לאינטראקציה, מוסיפות מידע המאפשר ניבוי טוב יותר של דיווחי שביעות הרצון של הלקוחות. יתרה מכך, המידע שניתן על ידי ההבעות הרגשיות של לקוחות ועובדים משמעותי יותר בניבוי שביעות רצון לאחר כשלון בתוצאת השירות, המייצג מצב של חוסר ודאות עבור הלקוחות. ממצאים אלה מבוססים על 23,645 אינטראקציות שירות אמיתיות, המכילות 277,000 הודעות של לקוחות ועובדים.

לסיכום, נתוני אינטראקציות שירות הנערכות בכתב ומאוחסנות באופן דיגיטלי והכלים האוטומטיים הקיימים היום לזיהוי הבעות רגשיות בטקסט מאפשרים הסתכלות ייחודית על דינמיקות של הבעות רגשיות בשירות לקוחות, תובנות שלא התאפשרו עם שיטות המחקר המסורתיות. ממצאי עבודה זו ממחישים את התובנות שניתן להרוויח מניתוח ההבעות הרגשיות של שני הצדדים באינטראקציה ברמת ההודעה הבודדת על מנת לשפר את ההבנה של תוצאות האינטראקציה. חוקרים המתעניינים בהשפעות של הבעות רגשיות יכולים ללמוד עליהן ללא צורך בגישות חודרניות או הסובלות מהטיות שונות ולבחון את השערותיהם במדגמים גדולים המאפשרים תוקף חיצוני גבוה ושחזור של ממצאי המחקר בעלויות נמוכות. מנהלים יכולים להשתמש בכלים טכנולוגיים כדי לנטר באופן רציף את ההבעות הרגשיות של לקוחות ועובדים ולזהות באופן מיידי מקרים של חוסר שביעות רצון של לקוחות ועומס עבודה גדול על העובדים.

ולהגיב אליהן באופן מותאם. דרישה זו נבחנה בשני מחקרים המבוססים על שיטות שונות: אחד המבוסס על נתוני שדה וההבעות הרגשיות בו מנותחות על ידי כלי אוטומטי ואחד המבוסס על נתוני מעבדה וההבעות הרגשיות בו מדורגות על ידי צופים. בשני המחקרים נמצאה תמיכה לכך שבנוסף להבעות רגשיות חיוביות על ידי עובדי השירות, תגובותיהם מותאמות להבעות הרגשיות של הלקוחות. במחקר הראשון נבחנו נתוני שדה הכוללים 1,320,392 הודעות של לקוחות ועובדים מ-164,899 אינטראקציות שירות לקוחות אמיתיות שנערכו דרך צ'ט. במחקר זה נעשה שימוש בכלי אוטומטי לזיהוי ההבעות הרגשיות בצ'אט ונמצא שעובדים משיבים באופן שתלוי בהבעות הרגשיות של שותפיהם לאינטראקציה (Response-Dependence) במידה רבה יותר מאשר לקוחות פועלים באופן דומה. לעומתם, לקוחות עקביים יותר בהבעותיהם הרגשיות במהלך האינטראקציה. כלומר, מידת תלות התגובה בהתנהגות הרגשית של שותפם לאינטראקציה שונה בין עובדים ולקוחות. במחקר השני, נאספו 102 סימולציות של אינטראקציות שירות כדי לתקף את ממצאי המחקר הראשון ולהרחיבם על מנת לבחון האם ההבעות הרגשיות של העובדים שמותאמות להבעות הרגשיות של הלקוחות משפרות את תוצאות האינטראקציה. במחקר זה נמצא כי עובדים מביעים יותר שמחה בתגובה להבעות שמחה של לקוחות. בנוסף, נמצא שכאשר לקוחות מביעים אכזבה, עובדים מביעים פחות שמחה ויותר אמפתיה בתגובה. ממצאים אלה מעידים כי עובדים אכן מתאימים את ההבעות הרגשיות שלהם להבעות הרגשיות של הלקוחות. עוד נמצא במחקר כי תגובת האמפתיה של העובדים בתגובה לאכזבת הלקוחות מובילה בתורה ליותר הבעות שמחה מצד הלקוחות. בנוסף, תגובותיהם של העובדים אכן נתפסו על ידי המדרגים כתלויות בתגובותיהם של הלקוחות במידה רבה יותר מאשר המצב ההפוך. לבסוף, נמצא שככל שמידת התגובתיות של העובד נתפסה כגבוהה יותר, כך שביעות הרצון של הלקוח הייתה גבוהה יותר. כלומר, ממצאי פרק זה מעידים שעובדים אכן מתאימים את תגובותיהם להבעות הרגשיות של לקוחות והתאמה זו, בתורה, משפרת את תוצאות הלקוח.

בפרק השלישי של עבודה זו נבחן הקשר בין הבעות רגשיות של לקוחות ועובדים במהלכן של אינטראקציות שירות ודיווחי שביעות הרצון של הלקוחות לאחר סיומן. בהתאם לגישת ה"תחושה כמידע" (Affect as Information), ממוצע ההבעות הרגשיות של הלקוחות נמצא כמסייע בניבוי הערכות שביעות הרצון כפי שדורגו על ידי הלקוחות לאחר האינטראקציה. בנוסף, בהתאם למודל ה"שיא והסיום" (Peak and End Model), הבעת הרגש הגבוהה ביותר (הבעת השיא) והבעת הרגש האחרונה (הבעת הסיום) של הלקוחות נמצאו כמוסיפות מידע המסייע

של הלקוחות והעובדים או הטיות הנפוצות במחקר המערב מדידות סובייקטיביות. בעבודה זו יוצגו תובנות וממצאים המתאפשרים על ידי שימוש במשאבים אלה.

עבודה זו כוללת שלושה פרקים. בפרק הראשון של עבודה זו מוצגות תובנות תיאוריות שניתן להשיג משימוש במשאבים דיגיטליים המאוחסנים כיום באופן שגרתי על ידי חברות ומשימוש בכלים אוטומטיים לניתוח הבעות רגשיות בטקסט. בפרק זה מוצגים ניתוחים המבוססים על נתונים של מעל 200,000 אינטראקציות שירות לקוחות אמיתיות, הכוללות מעל 2,000,000 הודעות של לקוחות ועובדים. הפרק סוקר דינמיקות של אינטראקציות שירות ומציג תובנות ראשוניות שניתן ללמוד מהן. הנתונים מעלים כי אינטראקציות שירות מתחילות באופן ניטרלי על ידי לקוחות ומסתיימות באופן חיובי יותר. כמו כן, ניכר כי עובדים פותחים אינטראקציות שירות באופן חיובי, ממשיכים אותן באופן ניטרלי ומסיימים אותן באופן חיובי שוב. דפוסים אלה מציעים כי לקוחות ממוקדים בפתיחת האינטראקציה בהבעת צרכיהם ולכן אינם מציגים הבעות רגשיות משמעותיות, אך מסיימים את האינטראקציה בהבעה רגשית שייתכן ומסמלת את שביעות רצונם מהטיפול בפנייתם. עוד ניתן ללמוד מכך כי עובדים מתחילים אינטראקציות באופן חיובי שייתכן ומעיד על הצגת ברכת שלום ללקוחות. לאחר מכן עובדים ככל הנראה מטפלים בצרכיהם של הלקוחות ובסופה של האינטראקציה, העובדים נפרדים מהלקוחות באיחולים חיוביים כמצופה מהם על ידי הארגון. עוד ניתן ללמוד מהנתונים כי דפוסים אלה אינם משתנים בשעות שונות במהלך היום, או בימים שונים במהלך השבוע. נתונים אלה מעידים בנוסף כי לקוחות המדווחים על שביעות רצון גבוהה יותר לאחר האינטראקציה הציגו הבעות רגשיות חיוביות יותר במהלך האינטראקציה, נתון הרומז על כך שניתן ללמוד על שביעות רצונם של לקוחות מהטקסט אותו הם מביעים במהלך האינטראקציה. בחינת הנתונים מנקודת המבט של העובדים, לעומת זאת, מאפשרת ללמוד על תדירות ההבעות הרגשיות שהם מציגים כחלק מעבודתם ועל השכיחות הגבוהה בה הם נחשפים במהלך המשמרת להבעות רגשיות על ידי לקוחות. תובנות אלה ממחישות את מורכבות עבודת נותני השירות.

בפרק השני של עבודה זו מנותחת מידת התגובתיות של לקוחות ועובדים להבעות הרגשיות של שותפם לאינטראקציה. כחלק מתפקידם, עובדי שירות לקוחות נדרשים לבצע "עבודת רגשות", כלומר, להציג רק הבעות רגשיות המאושרות על ידי הארגון. בפרק זה מוצגת הדרישה הפחות מוכרת של עבודת הרגשות הנדרשת מעובדי שירות: בנוסף לצורך להביע רגש חיובי במהלך מתן השירות, על העובדים לנטר את ההבעות הרגשיות של הלקוחות

הבעות רגשיות באינטראקציות שירות לקוחות - תקציר

הבעות רגשיות (כלומר, הבעות של רגש, מצבי רוח ועמדות) הן שכיחות באינטראקציות שירות לקוחות. לקוחות פונים לשירות עם בקשות ולעיתים עם תלונות אותן הם מציגים לעובדים ופניות אלה מלוות לעיתים בהצגת הבעות רגשיות כגון הבעת כעס בגין טיסה שבוטלה, הבעת שביעות רצון ממוצר שנרכש וכדומה. במקביל, חלק בלתי נפרד מתפקידם של עובדי השירות הוא לטפל בצרכי הלקוחות ולהציג הבעות רגשיות הולמות כפי שנדרש על ידי הארגון. מרבית המחקרים שנעשו עד כה בנושא אינטראקציות השירות מדדו הבעות רגשיות באופן חד-פעמי (למשל, האם הלקוחה הביעה את כעסה במהלך אינטראקצית השירות) או על ידי סכימה של כמות ההבעות הרגשיות במהלך האינטראקציה (למשל, מספר הפעמים בהם העובדת חייכה אל הלקוחה במהלכה). עם זאת, אינטראקציות שירות (ואינטראקציות חברתיות בכלל) הן מורכבות וכוללות דינמיקות שונות בין שני הצדדים לאינטראקציה. לדוגמא, לקוחה יכולה להביע את אכזבתה בתחילת האינטראקציה בגלל מוצר לא תקין, בהמשך להתמקד בפרטים טכניים ולתארם ללא הבעות רגשיות כלל, ובסוף האינטראקציה להביע את שביעות רצונה מהטיפול בפנייתה. ניתוח של הבעות רגשיות באינטראקציות שירות ללא התייחסות לדינמיקות המורכבות המתקיימות במהלכן עלול לפספס תופעות חשובות שלא ניתן לזהות בבחינה של אינטראקציות כפי שנעשתה בעבר.

בעבודה זו נבחנות ההשפעות של הבעות רגשיות של לקוחות ועובדים במהלך האינטראקציה על תוצאות שונות במהלכה ולאחריה. על מנת לקחת בחשבון את הדינמיקות המורכבות של הבעות רגשיות במהלך אינטראקציות שירות, עבודה זו מתמקדת בניתוח הבעות ברמת ההודעה הבודדת של אינטראקציות מבוססות טקסט (ספציפית, אינטראקציות שירות הנערכות דרך צ'ט). נתוני אינטראקציות שירות כתובות נשמרים כיום על ידי חברות באופן דיגיטלי ומאפשרים גישה לטקסט הנכתב על ידי לקוחות ועובדים. בעבודה זו נעשה שימוש בכלים טכנולוגיים שפותחו בשנים האחרונות ומאפשרים ניתוח אוטומטי של ההבעות הרגשיות המופיעות בטקסט. שמירת נתוני האינטראקציות באופן דיגיטלי והאפשרות לנתחם באופן אוטומטי מאפשרים לחוקרים גישה להבעות הרגשיות של לקוחות ועובדים במדגמים גדולים של אינטראקציות שירות הלקוחות מהעולם האמיתי. לפיכך, מתאפשרת מדידה אובייקטיבית ולא חודרנית של הבעות רגשיות, המתבססת על הטקסט המדוייק של הכותבים, ללא התערבויות הכוללות דיווחים עצמיים

המחקר נעשה בהנחייתן של פרופ' ענת רפאלי ופרופ"ח גלית יום-טוב בפקולטה להנדסת תעשייה וניהול ע"ש וויליאם דוידסון.

אני מודה לטכניון, קרן הווארד ואן גוטליב, וקרן משפחת קראון על התמיכה הכספית הנדיבה בהשתלמותי.

הבעות רגשיות באינטראקציות שירות לקוחות

חיבור על מחקר

לשם מילוי חלקי של הדרישות לקבלת תואר דוקטור לפילוסופיה

שלי אשתר

הוגש לסנט הטכניון - מכון טכנולוגי לישראל

סיוון תשפ"א חיפה מאי 2021