Modeling Employee Behavioral Reactions to Emotions Expressed by Customers: A Non-Obtrusive Examination of Customer Service Employee Behavior

Research Thesis

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1. Abstract

Service delivery relies on interactions with customers, which can be done through various contact channels including face-to-face, call centers, internet chats, and social networks (e.g. Twitter). The operation of customer contact centers is highly complex and must balance service quality with an efficient use of resources. A critical issue in this context, about which little is understood, is the influence of the behavior of customers, namely customer emotion expression, on employee efficiency. In the current research we use chat-interaction data provided by LivePerson Inc. (https://www.liveperson.com). Our analyses show intriguing findings: (a) employees respond more quickly to customers who express mild positive emotion or mixed emotion, (b) employees respond more slowly to customers who express highly negative or positive emotion, (c) expression of positive or negative emotion by customers moderates the impact of workload on employee speed of performance. In a second study, we examine the direction of these effects. In order to do so, we developed a sampling method in which customer messages are randomly selected and consequent employee responses are recorded, thus allowing us to examine the causal relationship between customer emotion and employee responses. Results show that increased positive emotion of customers led to quicker employee responses in consequent messages. Contributions to theory and practice are discussed and suggestions to future research are made.

List of Abbreviations and Notations

Abbreviations

LIWC - Linguistic Inquiry and Word Count

NPS – Net Promoter Score

RT - Response Time

AET - Affective Event Theory

BBT - Broaden and Build Theory

ST – Employee “Service Time”

OT – Employee “Other Time”

OWR – Other Words Read

OWW – Other Words Wrote

Notations

$EmoVal$ - A categorical variable representing chats where coded as “positive,” “negative”, “mixed” or “no-emotion” based on the average of the sentiment in the chat.

$EmoInt$ - Mean of intensity of emotion expressed by a customer in a specific chat regardless of whether the emotion was positive or negative.

$McustWords$ - Mean number of customer words in a selected time period.

$employeeRT$ - The mean duration it took employees to respond to a focal customer.

$ChatD$ – Chat duration.

$MempWords$- Mean number of employee words in a selected time period.

$customerRT$ - Mean customer response time in a selected time period.

u_i - The unique addition of each employee i to the intercept γ_0.

$x_{i,j}$ – A matrix of control variables.

Pos – Positive customer emotion as calculated by Equation 3.

Neg – Negative customer emotion as calculated by Equation 4.

2. Introduction

Emotions are inherent to human communication (Reis & Collins, 2004), conveying social information cues (Van Kleef, 2009), serving important social functions (Niedenthal & Brauer, 2012), and helping people adapt their behavior to a given situation (Van Kleef, Homan, & Cheshin, 2012). Emotion expression accompanies communication, which increasingly occurs in writing, through various technological media, such as WhatsApp, Twitter and Facebook. Such technologies are used by children to communicate with their parents (through WhatsApp), co-workers with each other (through emails, WhatsApp or Slack), fans with their favorite celebrities (through Twitter or Facebook), and service organizations with customers (through chat, Twitter or Facebook). These text-based interpersonal exchanges are increasingly popular, and inevitably include expressions of emotion (Fisher, 2013; e.g., Fisher, Rupová, & Bittnerová, 2014). Ofcom (2013) for instance reports that people communicate more through written media (e.g., e-mails, SMS, chat) than through voice technologies; IDC (2016) reports 435 million smart mobile devices in the US, while the total US population is only about 330 million. Using these devices, users access messaging applications five times per day on average.

A parallel trend of technological developments enables automatic identification of emotion from text (Pang & Lee, 2008). This trend suggests exciting opportunities for the study of emotion; spontaneous written communication is typically and relatively easily stored, so tools for automated linguistic analyses, such as Pennebaker’s Linguistic Inquiry and Word Count (LIWC; Tausczik & Pennebaker, 2010), can be used to study emotion evident in Twitter data (cf., Nakov, Ritter, Rosenthal, Stoyanov, & Sebastiani, 2016; Zhang, Ghosh, Dekhil, Hsu, & Liu, 2011) and written conversations (Bak, Kim, & Oh, 2012; Garas, Garcia, Skowron, & Schweitzer, 2012; Kanavos et al., 2014; Kim, Bak, & Oh, 2012). As noted by Rafaeli et al. (2016), the increased use of text-based communication together with the development of automatic text analysis tools, and sentiment analysis tools in particular, provide exciting opportunities for the study of emotion in customer service. The focus of the current work is therefore on the effects of emotion expressions in customer service; the novel methodological angle of this work is the use of natural written communication, analyzed by an automated sentiment analysis engine.

Zooming in on customer service, the extremely high operational costs are evident. A 2013 Forbes report notes that U.S organizations spend $112 billion on call center labor and software for some 270 billion customer-service calls; yet half of the requests each year remain unfulfilled (Upbin, 2013). This is a huge cost and there are different approaches aiming to reduce it. One of the relatively easy-to-implement solutions is development of self-service platforms, which enables customers to manage their own account without the help of a service employee. Another solution is providing service through new channels. Our focus here is on service through chat (cf., www.liveperson.com). The main operational difference between traditional service channels (i.e., face-to-face, call centers) and service through chat is that in the former service employees can address only one customer at a given moment, while chat allows one employee to serve multiple customers simultaneously. This allows increased flexibility, reduced employee idle time and increased efficiency. This explains the increasingly growing reliance on service through chat (Messina, 2016). Another explanation, as noted by IDC (2016), is that communication through written communication, or "messaging" has reinforcing benefits for both sides; customers enjoy a familiar, accessible and less intrusive mean of communication (compared with physical presence at the service provider's location or annoying call-center queues), while companies enjoy superior responsiveness to customers. The rich data recorded individually for each customer makes it possible for organizations (or other individuals) to analyze it further. From the perspective of studying emotion effects in customer service, this rich storage of data about customer interactions opens new research opportunities.

2.1 Emotion Display and Its Impact on Behavior in Interpersonal Business Exchanges

Emotion can impact individuals' behavior on different levels; intrapersonal, where individuals' own emotion impacts their own behavior (cf., Lyubomirsky, King, & Diener, 2005) and interpersonal, where individuals' emotion impacts others (cf., Barsade & Gibson, 2012; Hareli & Rafaeli, 2008). The focus of the current work will be on the latter.

Emotion expressions of one person can impact the behavior and cognition of the interaction party. For instance, it was found that displays of emotion can be used by individuals to manipulate their environment and to promote their own goals (Van Kleef, van den Berg, & Heerdink, 2015). In negotiation for instance, it is beneficial under some conditions to express anger (Reed, DeScioli, & Pinker, 2014; Tamir & Ford, 2012; Van Kleef, De Dreu, & Manstead, 2004), gratitude (Jia, Tong, & Lee, 2014) and disappointment (Lelieveld, Van Dijk, Van Beest, & Van Kleef, 2013). Whether genuine or not, emotion displays seem to influence interaction partners (Miron-Spektor, Efrat-Treister, Rafaeli, & Schwarz-Cohen, 2011; Van Kleef & Côté, 2007; Wang et al., 2013).

Emotion displays have varying impacts on targeted individuals within social interactions (Parrott, 2001). For example, effects of a positive emotion such as happiness, which is a desired emotion, may vary between individuals. Exposure to positive emotion was found to build one's social and cognitive resources (Fredrickson, 1998) and ultimately lead people to success (Lyubomirsky et al., 2005). However, it also has a "dark side". Positive emotion has some negative outcomes on individuals when it is too intense, inappropriately displayed or wrongfully pursued (see Gruber, Mauss, & Tamir, 2011 for review).

On the negative side of emotions, a striking case is *anger*; Van Kleef and Côté (2007) found that anger could hamper or contribute to one's goals depending on the appropriateness of the expressed anger and the power dynamics within a dyad. However, these studies have two major limitations: (a) they are context specific—a laboratory negotiation—and do not necessarily represent all interpersonal business exchanges. Therefore, they lack external validity. (b) They manipulate emotions dichotomously (present or absent) and do not consider the fact that emotion can appear in different levels of intensity—which is likely relevant to the effect of actors' emotion expression on partners' behavior (Glikson, Rafaeli, Wirtz, & Kopelman, 2015). In natural communication, however, emotion can fluctuate throughout an interaction with different intensity.

Another example of negative emotion in business interactions is found in customer service. Many service employees regularly experience verbal and even physical abuse by customers while interacting with them (Barling, Dupré, & Kelloway, 2009; Grandey, Dickter, & Sin, 2004; Harris & Reynolds, 2003; Kern & Grandey, 2009; Landau & Bendalak, 2008; McColl-Kennedy, Patterson, Smith, & Brady, 2009) . This customer behavior, induced by negative emotions such as anger and stress (Sprague, Verona, Kalkhoff, & Kilmer, 2011), can have major consequences for staff well-being (Grandey, Rupp, & Brice, 2015), operational costs (Grandey et al., 2015), and service quality to other customers in the system

(Lim, Cortina, & Magley, 2008; Tao, Karande, & Arndt, 2016). Research shows that employees who are exposed to customer expressions of anger may provide poorer service to the same customer as well as to other customers (Tao et al., 2016). In contrast, however, there is some evidence suggesting that customer service employees reward customers who express higher levels of anger (Glikson et al., 2015) compared with customers who express embarrassment or no emotion (Derfler-Rozin, Rafaeli, Ravid, & Weber, 2016). Service research also shows that customer expression of anger towards customer service employees, reduces employee task performance through the toll it takes on cognitive resources (Rafaeli et al., 2012). This finding was further supported by Wang et al. (2013), who found that constant exposure to negative emotion induced rumination and negative mood among employees, which can hamper executive functioning (Philippot & Brutoux, 2008) and by extension, employee performance. However, the studies outlined above suffer from a major limitation—they mostly use non-objective measures such as self-reports that have some problematic shortcomings (Donaldson & Grant-Vallone, 2002; Paulhus & Vazire, 2007).

Another important fact that ought to be considered is that some conversations can entail both positive and negative emotion (i.e., *mixed emotion*) and a conversation that started with negative expressions might, at some point, also include positive messages and vice versa. The concept of mixed emotion was defined by Larsen, McGraw and Cacioppo (2001) as the co-existence of emotions that are polar opposites on the emotion circumplex model (see Berrios, Totterdell, & Kellett, 2015 for a meta-analysis). Studies show that mixed emotion has a unique effect on individuals, especially in an organizational context. Mixed emotion can increase creativity, thus allowing employees to identify unique and unusual assosiations between events (Fong, 2006). Mixed emotion can also increase judgment accuracy by increasing peoples' receptivity, alternative perspectives and their tendecy to consider them (Rees, Rothman, Lehavy, & Sanchez-Burks, 2013) thus allowing employees to perform better. However, to this date there is almost no research on mixed emotion in interpersonal exchanges. If so, an accurate analysis would address the possibility of multiple or mixed emotions in conversations, as we do in the current research.

In short, available literature offers only a limited understanding of the full complexity of emotion in business interactions, for multiple reasons: (1) most available research has been on negotiation interactions, which is a very specific form of interaction and does not represent the full range of interaction types in a business context; (2) research has mostly examined behavior in laboratory settings with little empirical studies of spontaneous, real-life interactions; (3) lab experiments did not manipulate different intensities of expressed emotions; (4) a large portion of the literature presented above has relied heavily on self-report measures that suffer from many limitations and (5) there is limited consideration of the presence of mixed emotions.

To begin filling in these gaps, the current work will examine genuine real-life interactions between customers and employees where all measures are objectively recorded without any use of self-reports. Customer service interactions are fundamentally social interactions (Brotheridge & Grandey, 2002; Czepiel, 1990; McCallum & Harrison, 1985). The goals of these conversations range from mundane requests on a variety of subjects to emotionally intense interactions regarding financial issues and various frustrations. Moreover, the data of our study will be text-based, customer service interactions (chats), which afford a direct access to expressed emotions. The study will be carried out through the use of an automatic home-grown sentiment text analysis engine, substantially reducing the effects of "experimental noise" and the extreme difficulties of manually coding naturally occurring interactions. The long-term goal of our work is a comprehensive understanding of emotion unfolding in human interactions; the current work will address the following question: What are the behavioral influences of expressions of emotion by one communication partner (customer) on the other (employee)?

We can model this question as follows: When individuals I_1 and I_2 interact, what would be the influence of emotion $E_{1,2\ldots k}$ of I_1 (with intensity X) on individual I_2's behavior? To address this question, information about the context of the interaction is required. While such information might be hard to extract from random human-to-human interactions, it is continuously recorded in written customer service systems, where details about employee and customer actions are typically stored.

2.2 Customer Emotion and Employee Performance – Hypotheses Development

One robust way to measure employee performance is to ask customers to rate their service experience using self-report tools, such as the Net Promoter Score (NPS; Reichheld, 2003). Such self-reports are highly prevalent in the industry (Kaplan, 2016) as well as in research (cf., Giardini & Frese, 2008; Grandey, Goldberg, & Pugh, 2011). However, this method has some substantial limitations, beyond the limitations of self-reports we mentioned before (Donaldson & Grant-Vallone, 2002). For instance, since employees are often evaluated and rewarded according to the self-reported satisfaction of their customers, in some cases bribery is offered to customers so that they provide high rankings (Kaplan, 2016). This has led industry officials to question the veracity of such measures, neglect their reliance on them and call for new methods to assess customer service employee performance (Kaplan, 2016).

A direct and objective approach to measure employee performance in chat interactions could be a measure of employee Response Time (RT) to customers. Although it is only one specific aspect of the service, it is a very important one for customers as well as for service organizations. From customers' perspective, employee RT is of high importance since low RT keeps the service flow and ultimately saves customers time. This measure is also important from the organizational side, since faster service means high employee productivity and reduced operational costs. Therefore, in the current research we refer to employee RT as an objective measure of employee performance.

If so, the question we are interested in is what are the effects of emotion expressions of customers on Employee RT. A few types of psychological theories are relevant in answering such a question. The current work regards the following two: the first type deals with cognitive processes that ultimately affect and govern one's behavior and the second type deals with employee motivations. Both types of theories have conflicting predictions regarding our research question. Moreover, conflicting predictions exist even within theories with a cognitive approach, as we present in the following sections. Each section introduces conflicting predictions made by the two types of theories mentioned above regarding the effect of customer emotion on employee behavior.

Effects of the Presence of Customer Emotion on Employee RT

A relevant theory in that context should take into account the effect of emotion on cognitive processes. Affective Event Theory (AET; Weiss & Cropanzano, 1996) asserts that work-related events (even mundane) carry emotion-inducers that require employees to process them, and hence reduce the availability of cognitive resources needed for performance—a notion that was further supported in theoretical (Beal, Weiss, Barros, & MacDermid, 2005) and empirical work (see Iordan, Dolcos, & Dolcos, 2013 for a review on neuroscience evidence). For example, it was found that exposure to positive or negative emotion narrows one's attention (Gable, Poole, & Harmon-Jones, 2015) and such a limited attention capacity is likely to prolong the service process. Therefore, a slower employee RT is expected when emotion is introduced:

Hypothesis 1.1:

Expression of an emotion by customers, regardless of whether the expressed emotion is positive, negative or mixed, leads to higher employee RT compared with no expressions of emotion.

However, it is also plausible to expect reduced employee RT following exposure to emotion since there is evidence for perceptual (Ohman, Lundqvist, & Esteves, 2001; Pourtois, Grandjean, Sander, & Vuilleumier, 2004) and cognitive (Talarico, LaBar, & Rubin, 2004) enhancement induced by emotion (see Dolcos & Denkova, 2014 for review). The Broaden and Build Theory (BBT; Vacharkulksemsuk & Fredrickson, 2013) deals specifically with enhancements as a result of positive emotion, and contrary to the AET, it recognizes positive emotion as facilitating employee performance by broadening attention and "building" an additional cognitive-resource necessary to perform. This means that when customers express positive emotion, employees are predicted to benefit from it and hence respond faster than when customers express negative or no emotion.

Hypothesis 1.2:

Expression of positive emotion at any level of intensity by customers will reduce employee RT.

Customer negative emotion in service interactions has been suggested as benefiting customers who express it (Derfler-Rozin et al., 2016; Glikson et al., 2015). Regulatory focus theory (Higgins, 1997, 1998) asserts that there are two types of mindsets that govern individuals' behavior; "prevention focus" is when individuals' behaviors are aimed at avoiding aversive situations and "promotion focus" is when individuals' behaviors are aimed at pursuing pleasant situations. Regulatory focus theory would suggest that customers' expression of negative emotion makes employees "prevention focused" (Miron-Spektor et al., 2011), meaning that they will act to avoid such unpleasant interactions. In the context of customer service, this can explain why customers are rewarded for expressing negative emotion—employees seek to shorten the interaction with such customers, thus attend to their requests faster in order to complete the interaction as soon as they can. In this respect, we predict that employees will respond faster to customers who express negative emotion. However, in the context of chat service, where employees interact with multiple customers, employees can avoid customers who express negative emotion by working with other customers. In this case, employee RT is expected to increase when exposed to customer negative emotion. Hence, our next hypothesis is two-tailed:

Hypothesis 1.3:

Expression of negative emotion at any level of intensity by customers will impact employee RT.

The mixed emotion literature further challenges AET and Hypothesis 1.1 and suggests enhanced performance by employees who are exposed to mixed emotion (Fong, 2006; Rees et al., 2013), compared with no exposure to emotion. For instance, in a lab experiment where participants were induced with different kinds of emotion, the mixed emotion group scored higher on a test designed to measure divergent and creative thinking (Fong, 2006). Therefore, we expect to find faster employee RT when customers express mixed emotion compared with customers who express no emotion. So a hypothesis that competes with Hypothesis 1.1 is as follows:

Hypothesis 1.4:

Expression of mixed emotion by customers at any level of intensity will reduce employee RT.

Effects of Customer Emotion Intensity on Employee RT

So far, our predictions regarded the effects of the mere presence of different types of emotion at any level of intensity on employee RT. The following set of predictions regards the intensity of different types of emotion. Following Hypothesis 1.1, we predict an increase in employee RT in interactions with greater emotion intensity, regardless of emotion type, since employees who are exposed to emotion are required to process more information, thus leaving less cognitive resources for work tasks (Weiss & Cropanzano, 1996):

Hypothesis 2.1:

Regardless of the valence of expressed emotion (positive, negative or mixed), increase in customer expressed emotion intensity will lead to an increase in employee RT.

However, based on the different effects of positive, negative and mixed emotions on individuals predicted above (Hypotheses 1.1, 1.2, 1.3 and 1.4), it is also plausible to predict that the relationship between emotion intensity and employee RT would be different depending on the type of emotion expressed. Namely, an increase in negative emotion is predicted to be associated with an increase in employee RT, while positive and mixed emotion intensity is predicted to be associated with a decrease in employee RT:

Hypothesis 2.2:

The relationship between customer expressed emotion intensity on employee RT depends on the valence of the expressed emotion such that an increase in negative emotion intensity will <u>*increase*</u> *employee RT while an increase in positive or mixed emotion intensity will* <u>*decrease*</u> *employee RT.*

Moderating Effects of Customer Emotion on the Workload-Performance Relationship

The predictions we presented so far deal with effects of different types of emotion and emotion intensity on employee RT. The following set of hypotheses will deal with the moderation effects that emotion might have on the relationship between workload and employee performance (RT). Kc and Terwiesch (2009) show that in healthcare systems, at first, workload is negatively related to service rate. That is, when workload increases, employees speed up their work and service rate increases. However, this effect does not hold for long. When workload is high for long periods of time, employees slow down and service rate ultimately <u>decreases</u>, suggesting that employees have longer RT that is predicted by high workload. Fritz and Sonnentag (2006) show, from a sample of university employees, a negative relationship between workload and performance such that higher workload was associated with lesser performance. Also, in restaurants (Tan & Netessine, 2014), waiters who experienced increases in workload gave slower service to customers. A preliminary check shows that in our data the slowdown in agent service rate is more pronounced, as shown in the latter two papers. Therefore, we expect to find a positive relationship between employee workload and employee RT. Our interest, however, is in the moderating effect emotions might have on this relationship. As before, different psychological theories suggest different predictions, as we elaborate next.

The Borden and Build Theory (BBT) suggests that when exposed to positive emotion, employees benefit from cognitive enhancements and increased mental resources required for them to perform (Vacharkulksemsuk & Fredrickson, 2013). Since enhanced cognitive abilities could assist employees to cope with increased workload, we would expect to find a moderation effect of positive emotion on the relationship between workload and employee RT as follows:

Hypothesis 3.1:

*Positive emotion will moderate the impact of workload on employee RT such that the impact of workload and employee RT is **reduced** when employees are exposed to positive emotion compared with exposure to negative emotion or no emotion.*

AET contradicts the BBT's prediction because it asserts that emotion requires employees to use their mental resources to process the emotion to which they are exposed (Weiss & Cropanzano, 1996) and therefore less resources should be available for employees to perform leading them to perform slower. Another claim that challenges the BBT is that positive emotion may lead to complacency, loafing and procrastination (Parrott, 2001) thus increasing employee RT. Based on this claim and AET, our next hypothesis competes with the former:

Hypothesis 3.2:

*Positive emotion will moderate the impact of workload on employee RT such that its impact is **increased** when employees are exposed to positive emotion compared with exposure to negative emotion or no emotion.*

In the case of negative emotion, the literature also fails to provide a clear prediction. On the one hand, Affective Event Theory suggests diminished performance as a result of exposure to negative emotion due to the toll emotion takes on employee mental resources.

However, in some cases, it was documented that performance was enhanced as a result of exposure to negative emotion (Miron-Spektor et al., 2011). In customer service, customer negative emotions are energizing because employees are appraised on and motivated to elicit positive emotions in customers (Pugh, 2001). Therefore another set of competing hypotheses is postulated:

Hypothesis 4.1:

*Negative emotion moderates the impact of workload on employee RT such that workload impacts employee RT **more** when employees are exposed to negative emotion compared with exposure to positive emotion or no emotion.*

Hypothesis 4.2:

*Negative emotion moderates the impact of workload on employee RT such that workload impacts employee RT **less** when employees are exposed to negative emotion compared with exposure to positive emotion or no emotion.*

The Moderating Effect of Customer Mixed Emotion on the Workload-Performance Relationship

In the case of mixed emotion, available research does not allow one to predict a specific direction. Although the benefits of mixed emotion on targeted individuals were previously documented (Fong, 2006), the effects of mixed emotion on performance while interacting with workload has not yet been explored, as far as we know. Therefore, the next hypothesis is two-tailed:

Hypothesis 5:

*Mixed emotion will moderate the impact of workload on employee RT such that its impact is **different** when customers express mixed emotion compared with no emotion.*

3. Study 1

3.1 Method

Data

The data for testing the hypotheses was provided by LivePerson Inc., a company that provides a service-platform that allows other companies to interact with their customers through chat (www.liveperson.com). We obtained a sample of 7,147 interactions between customers and service employees of a western airline company conducted in the first two weeks of December 2015. There are three types of entries in the data: employee lines, customer lines and system lines (see Figure 1). System lines are automatically generated messages that do not reflect any human behavior and therefore were removed from the data. The chats lasted an average of 11 minutes and 55 seconds (SD=8 minutes and 47 seconds), included an average number of customer messages of 5.16 (SD=4.04), and an average number of employee messages of 5.81 (SD=4.22). The analysis we present in the current study is based on an aggregation of the data to the chat level.

Data Structure

Each chat is identified by customer (encrypted) ID, employee ID, date, type of service (sales or customer service), and the time the customer waited before the service interaction started. Each message in the chat is represented by a single line in the data and includes a timestamp, who wrote that line (customer, agent or system), number of words, and sentiment score. Sentiment score is only available for customer messages and includes valence and intensity. Demographics of customers and employees are not available (the full set of variables and descriptive statistics are discussed below and in Table 1).

Chat with McCafee call center started @ 13:23:07. Full transcript can be found at : https://community.mcafee.com/thread/28171

SYSTEM: Welcome to McCafee. How may I help you?
Customer (13:37:46):
Hi. I purchaed a disk and it doesn't work.
Employee (13:41:33):
Please let me know the locations you purchased the CD.
Customer (13:41:46):
I've been waiting for this info for 20 mins.
Employee (13:42:00):
You can contact the McAfee Sales team at +91 80 6656 9000 to renew the McAfee software.
Customer (13:42:17):
Come on.
Customer (13:42:29):
Don't pass the bill.
Customer (13:42:46):
You're not answering my question.
Customer (13:43:05):
Can I chat with your supervisor?
Employee (13:43:22):
I apologize for the inconvenience.
Customer (13:43:33):
Can I have a chat with your supervisor?

Figure 1- An example of chat service interaction. "SYSTEM" lines are automatically generated messages, "Customer" lines are messages written by customers and "Employee" lines are messages that an employee wrote.

Variables

Identifying Emotion in Chat Interactions

The process of extracting and quantifying expressed emotion from text is called sentiment analysis (cf., Nakov et al., 2016). Most sentiment analysis tools were developed based on texts that are highly different from customer service texts. For instance, one of the state-of-the-art tools developed in Stanford is based on movie reviews (Socher, Perelygin, & Wu, 2013). Applying such tools to customer service texts and validating them against coding of human naïve judges reveals very low precision and recall[a] values, typically lower than 20% (Rafaeli, Ashtar, et al., 2016). We therefore relied on a sentiment analysis tool

[a] See (Lancaster, 1979) for an introduction on information retrieval.

developed and specifically tailored for customer service communication and validated by Rafaeli et al. (2016).

The tool builds on, and expands the capacity of, a tool known in psychological research, called Linguistic Inquiry and Word Count (LIWC; Tausczik & Pennebaker, 2010), as it is based on a word count of words that are associated with positive or negative emotion. The tool also accounts for grammatical context, such as negation words and "amplifiers" (e.g., "very"), and provides an output for each customer message sent in a chat comprised of emotion valance (positive or negative) and intensity (0 means no emotion detected, 1 is low and 7 is high intensity).

For example, the following sentence is coded as positive with intensity 2:

"That's enabled me to access my account. Thanks, that's really helpful."

In contrast the following sentence is coded as negative with intensity 2:

"Way too expensive for a local call I can go elsewhere ...!".

A validation study that used coding of human naïve judges revealed that the tool has a precision and recall[a] of 75% and 19% respectively for positive emotion. That is, in 75% of the cases in which the tool detected positive emotion, human coders also identified emotion (i.e., 25% "false alarms") and in 81% of the cases where human coders detected positive emotion, the tool did not (i.e., "misses"; Rafaeli, Ashtar, et al., 2016). For negative emotion, precision and recall were 75% and 20% respectively. We assume that this makes our analyses and results a conservative test of our hypotheses. Our analyses test the effects of only a part of the emotion in the data. This means that the reference group of chats assumed to have no emotion, may include some emotional influences that are not attributed to emotion and thereby increase statistical "noise".

<u>Independent Variables</u>:

(a) Emotion valence ("EmoVal"; positive/ negative / mixed/ no-emotion). A categorical variable representing chats were coded as "positive," "negative", "mixed" or "no-emotion" based on the average of the sentiment in the chat. That is, "positive" or "negative" chats carry mostly positive or negative emotion, respectively. "Mixed" has the same amount of positive and negative emotion and "no emotion" represents chats with no detected emotion (see Figure 2 and Figure 3).

(b) Mean emotion intensity of a chat ("EmoInt") is the mean of intensity of emotion expressed by a customer in a specific chat regardless of whether the emotion was positive or negative (M=0.27 , SD=0.36 , range 0 to 7; see Table 1).

(c) Mean number of customer words in a chat ("McustWords"; M=16.3, SD=9.41, range from 1 to 144; see Table 1).

Dependent Variable (DV):

Mean employee Response Time ("employee RT"); The mean duration it took employees to respond to a focal customer. This variable is a proxy for employee performance since long employee RT is associated with poorer service and increased operational costs (M= 78.5, SD=93.07, range from 1 to 2,673 seconds; see Table 1[b]).

Control variables:

(a) Day of week (63.42% weekdays and 36.58% weekends).
(b) Time of day (15.69% morning, 20.16% noon and 64.15% evening).
(c) Type of service (39.79% sales and 60.21% customer service).
(d) Employee ID (40 employees total).
(e) Time customer waited before chat ("Queue"; M=36.23, SD=93.77; range from 0 to 1,439 seconds; see Table 1).
(f) Chat duration ("ChatD"; M=715.16, SD=527.14, range from 44 to 6580 seconds; see Table 1).
(g) Mean number of employee words in a chat ("MempWords"; M=28.13, SD=13.77, range from 1 to 153; see Table 1).
(h) Mean customer response time in a chat ("Customer RT"; M=57.08, SD=40.21, range from 0 to 767 seconds; see Table 1).

[b] Table 1 presents the natural variables and Table 2 presents variables after transformation.

Statistical Analysis

The statistical method used in this study is Hierarchical Linear Model (HLM) using R (2014) and the 'lme4' (Bates, Mächler, Bolker, & Walker, 2015) and 'lmerTsts' (Kuznetsova, Bruun Brockhoff, & Haubo Bojesen Christensen, 2016) packages.

3.2 Results

Descriptive Statistics

Correlations, means and standard deviations are shown in Table 1 and Table 2. All non-categorical variables were Box-Cox transformed[c] as recommended in linear models where residuals are not normally distributed (cf., Hyndman & Grunwald, 2000 Appendix A for an example of distributions before and after transformation).

[c] A method of log transformation which allows one to keep zero values.

Table 1 - Means, standard deviations, and correlations among variables.

Variable	*Mean*	*SD*	1	2	3	4	5	6
1. ChatD	715.16	527.14						
2. employee RT	78.50	93.07	.28**					
3. MempWords	28.13	13.77	-.01	.38**				
4. EmoInt	0.27	0.36	.02	-.04**	.02			
5. Customer RT	57.08	40.21	.27**	.11**	.15**	.02		
6. McustWords	16.30	9.41	.05**	.18**	.25**	.25**	.34**	
7. Queue	36.23	93.77	.01	-.01	-.01	.03*	-.03**	.02*

Note. * *p* < .05; ** *p* < .01; *** *p<.001*. All variables are Box-Cox transformed.

Table 2 - Means, standard deviations, and correlations among transformed variables.

Variable	*Mean*	*SD*	1	2	3	4	5	6
1. ChatD	6.34	0.69						
2. employee RT	4.05	0.76	.44**					
3. MempWords	3.28	0.41	.07**	.38**				
4. EmoInt	0.21	0.23	.06**	-.06**	.01			
5. Customer RT	3.89	0.60	.40**	.18**	.16**	.01		
6. McustWords	2.74	0.47	.12**	.23**	.23**	.22**	.39**	
7. Queue	1.74	1.72	.00	.00	.00	.02	-.08**	.02

Note. * *p* < .05; ** *p* < .01; *** *p<.001*.

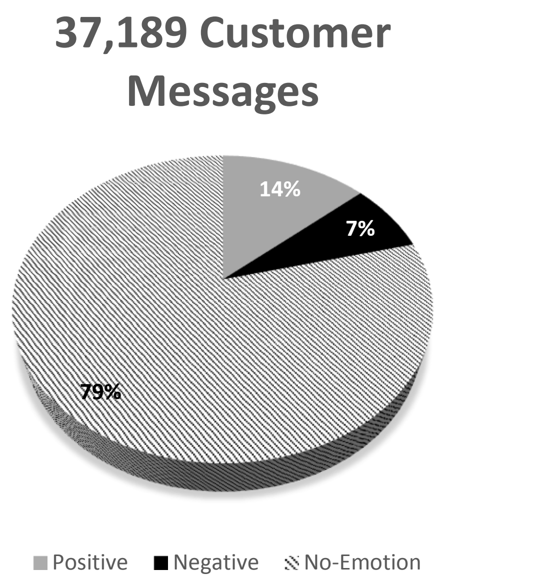

Figure 2 - Emotion distrubution at the customer line level

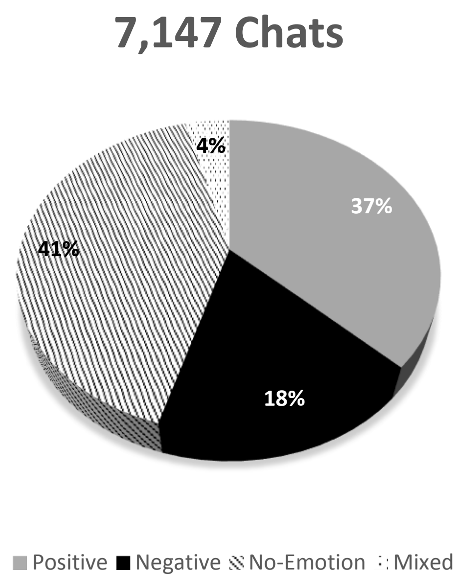

Figure 3 - Emotion distribution at the chat level

Hypotheses Testing

To decide which type of model fits best to our analysis—Ordinary Least Square (OLS) or Hierarchical Linear (HLM) Model—we calculated the Intraclass Correlation (ICC) between any two measurements of the dependent variable for the same employee. Results reveal a weak yet significant correlation (ICC=0.128, Wald Z=3.78, p<0.001) indicating that 12.8% of the variance in employee RT can be explained by employee ID alone. Hence, all hypotheses in this study are tested using an HLM approach, which accounts for the random effect employees have on the dependent variable, as each conversation is nested within an employee. All hypotheses were tested using the following model:

Equation 1:

$$\begin{aligned} log1p\left(employeeRT_{i,j}\right) &= \gamma_0 + u_i + \gamma_1 x_{i,j} + \gamma_2 EmoVal_{i,j} + \gamma_3 log1p\left(EmoInt_{i,j}\right) \\ &+ \gamma_4 log1p\left(McustWords_{i,j}\right) + \gamma_5 log1p\left(EmoInt_{i,j}\right) * \gamma_2 EmoVal_{i,j} \\ &+ \gamma_6 log1p\left(McustWords_{i,j}\right) \cdot EmoVal_{i,j} + \varepsilon_{i,j} \end{aligned}$$

Let i denote employee and j denote a chat; u_i is the unique addition of each employee i to the intercept γ_0; $x_{i,j}$ includes all control variables mentioned above. Results are presented in Table 3. AIC values for the null model (random effect), reduced model and full model are

15,241.5, 11,616.2 and 11,593.5 respectively, indicating that the full model has a better fit to the data than the other models. Therefore, the model we used to test our hypotheses is the latter.

Testing the Effects of the Presence of Customer Emotion on Employee RT

Hypotheses 1.1 and 1.2 have conflicting predictions regarding the effects of emotion on employee RT. Hypothesis 1.1 predicts an increase in employee RT due to increased usage of employee cognitive resources emotion evokes, regardless of emotion valence, and Hypothesis 1.2 predicts a decrease in employee RT in chats where employees are exposed to positive emotion. As presented in Table 3, and supporting Hypothesis 1.2, positive emotion is associated with decreased employee RT (γ=-0.41, $p<0.001$). The results show that when customers express positive emotion in a chat, there is a decrease of 33.63 seconds in employee RT on average for each message in the same chat.

In other words, when a customer expresses positive emotion, and an employee sends 5.81 messages (an average chat) the model predicts a reduction of 3 minutes and 15 seconds $(33.63 \cdot 5.81 = 195.39_{seconds})$ in total employee RT (compared to customers who express no emotion). Moreover, employees respond faster to customers who express positive emotion than to customers who express negative emotion (γ= 0.37, $p<0.001$; see Table 4 for all pairwise comparisons). Thus Hypothesis 1.2 is supported over Hypothesis 1.1.

There was no significant effect for negative emotion on employee RT (γ= -0.16, $p>0.05$); thus Hypothesis 1.3 is not supported. Mixed customer emotion, similar to positive emotion, did have a significant effect in reducing employee RT (γ= -0.73, $p<0.05$), with a reduction of 3 minutes and 54 seconds in RT over the whole chat compared to chats with no customer emotion. Moreover, employees respond faster to customers who express mixed emotion compared with customers who express negative emotion (γ= -0.50, $p<0.05$), supporting Hypothesis 1.4. Contrarily, there is no significant difference in employee RT between customers who express mixed emotion and customers who express positive emotion (γ=-0.13, $p>0.05$), thus partially supporting Hypothesis 1.4.

Testing the Effects of Customer Emotion Intensity on Employee RT

Hypothesis 2.1 predicts that an increase in emotion intensity will increase employee RT. As evident in Figure 3, 41% of the sample were chats with no identified emotion.

Including this group in testing the relationship between emotion intensity and RT is misleading, since one variable is a constant (emotion intensity is zero). A more accurate test is only of chats where emotion is present. In this estimation there is a highly significant positive relationship between emotion intensity and employee RT ($\gamma=0.33$, $p<0.001$; for the relevant regression analysis, see Appendix B), supporting Hypothesis 2.1.

Hypothesis 2.2 predicts that the relationship between emotion intensity and employee RT is different between emotions. Again analyzing only chats with some customer emotion[d], the interaction between emotion intensity and positive emotion was a significant predictor of employee RT when contrasted against negative and mixed emotion ($\gamma=0.42$, $p<0.001$ and $\gamma=0.56$, $p<0.05$, respectively; see Appendix B). A Simple Slop analysis, as presented in Figure 4, helps unravel this finding. As evident, an increase in the intensity of customer emotion is associated with an increase of employee RT. Surprisingly, when customers express mostly positive emotion, this increase is mitigated compared with customers who express mostly negative or mixed emotion, but is still positive, contrary to our prediction. No difference was found between negative emotion and mixed emotion slopes ($\gamma=0.14$, $p>0.05$; see Appendix D and Figure 4). Thus, Hypothesis 2.2 is partially supported (only the prediction about customer negative emotion is consistent with the results).

Testing the Moderating Effects of Customer Emotion on the Workload-Performance Relationship

The remaining hypotheses were tested using the interactions between mean customer words (McustWords) and the presence of positive/negative/mixed customer emotion ($\gamma=-0.11$, $p<0.01$; $\gamma=-0.19$, $p<0.001$; and $\gamma=-0.14$, $p>0.05$, respectively). Results support Hypotheses 3.1 and 4.2 and not Hypotheses 3.2, 4.1 and 5, since the impact of workload on employee performance varied as a function of the expressed emotion. As evident in Figure 5, when customers expressed no emotion, there is a clear and intuitive positive association between McustWords (a work demand employees have to heed, at least by reading), and employee RT. However, when customers express positive or negative emotion, the slope of this trend is significantly moderated. That is, more workload was associated with <u>less</u>

[d] Chats coded as "No emotion" are not a part of this analysis because their emotion intensity is a constant (0).

increase in employee RT when customers express positive or negative emotion. Results remain similar when analyzing only chats with emotion (Appendices B and C).

Table 3 - Hierarchical Linear Modeling (HLM) result testing all hypotheses of Study 1.

	DV = Employee RT					
	Null model		Reduced model		Full model	
	γ	*SE*	γ	*SE*	γ	*SE*
Intercept	4.01***	0.05	-0.63***	0.10	-0.79***	0.13
Variance Components						
Within-group variance (Level 1)	0.49					
Between-group variance (Level 2)	0.07					
Control Variables						
MempWords			0.49***	0.02	0.48***	0.02
Customer RT			-0.25***	0.01	-0.24***	0.01
Queue			-0.01***	0.01	0.01***	0.01
Type of Service: Sales[(a)]			-0.09	0.07	-0.09	0.07
ChatD			0.58***	0.01	0.58***	0.01
Time of day (Morning)[(b)]			-0.05**	0.02	-0.05**	0.02
Time of day (Noon)			0.01	0.02	0.01	0.02
Day of week[(c)]			-0.02	0.01	0.02	0.01
Independent Variables						
Positive emotion			-0.59***	0.02	-0.41***	0.08
Negative emotion			-0.43***	0.02	-0.04	0.11
Mixed emotion			-0.59***	0.04	-0.54**	0.23
EmoInt			-0.49***	0.02	0.33	0.27
McustWords			0.23***	0.01	0.10**	0.04
EmoInt X positive[(d)]					-0.36***	0.1
EmoInt X mixed[(d)]					0.33	0.26
McustWords X positive					0.12***	0.04
McustWords X negative					0.08	0.09
McustWords X mixed					0.18	0.04

-2 log likelihood	15,235.6	11,584.2	11,552.6
AIC	15,241.5	11,616.2	11,593.5
Pseudo-R^{2} [(e)]		41.08%	41.54%

Note. [(a)]Two types of employee work, where 1=Service, 0=Sales. [(b)]Compared with evening. [(c)]Weekdays compared with weekends. [(d)]Compared with Emotion intensity X negative emotion. [(e)]Pseudo-R^2 was calculated using the formula suggested by Snijders & Bosker (2012). ***p<0.001, **p<0.01, *p<0.05, †p<0.1

Table 4 - Coefficients representing a difference in employee RT as a function of the dominant emotion expressed in chats. Coefficients are obtained by changing the reference group dummy coded as "0".

	1. No emotion (dummy code=0)	2. Positive (dummy code=0)	3. Negative (dummy code=0)
1. No emotion	-	-	-
2. Positive (dummy code=1)	-0.41***	-	-
3. Negative (dummy code=1)	-0.04	0.37**	-
4. Mixed (dummy code=1)	-0.54*	-0.13	-0.50*

Note. ***p<0.001, **p<0.01, *p<0.05, †p<0.1

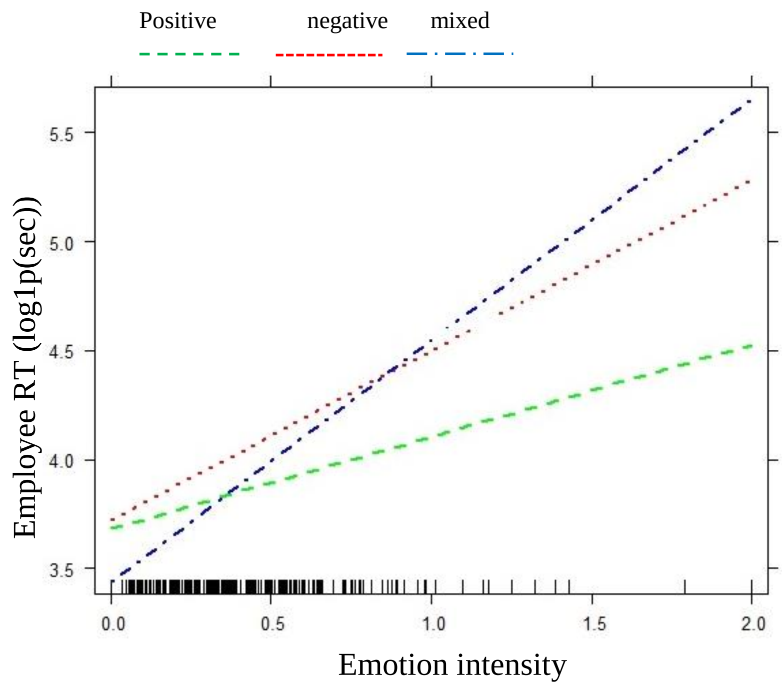

Figure 4 - Simple slopes of emotion intensity X emotion valence interaction. Variables on the Y and X axes are log1p() transformed.

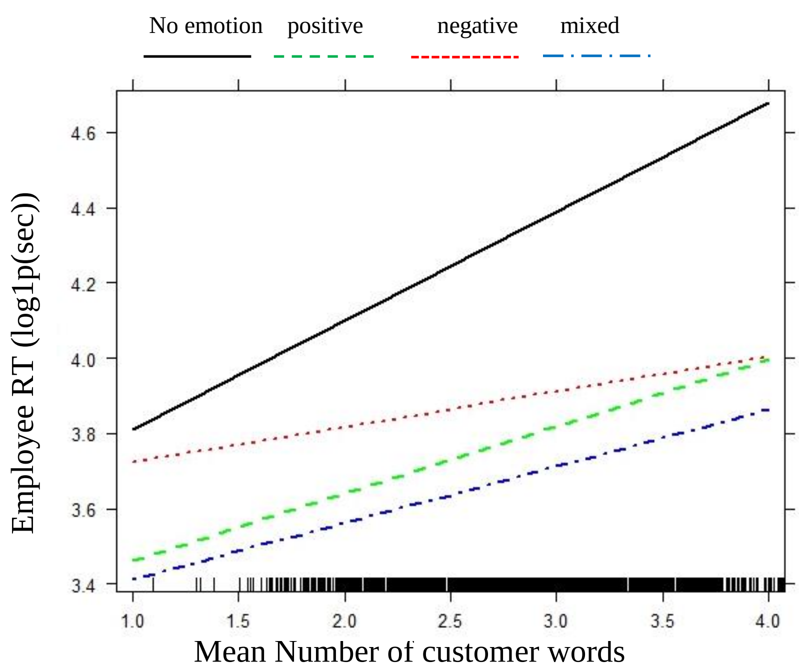

Figure 5 - Simple slopes of the Number of Customer Words X emotion valence interactions. Variables on the Y and X axes are log1p() transformed.

3.3 Discussion

Results of Study 1 show intriguing findings, suggesting the effects of customer emotion on employee response time (RT). We show that employees respond significantly faster to customers who express mostly positive or mixed emotion compared with customers who express negative or no emotion. These results support our predictions as developed and presented in Section 2.2. Specifically, Hypotheses 1.2, 2.1, 3.1 and 4.2 were supported and Hypotheses 1.4, 2.2 were partly supported. However, some competing arguments must be considered to understand the causal nature of these effects. First, it is plausible that the presence of positive or mixed emotion is confounded with task complexity. That is, one can claim that in chats with dominant positive emotion or mixed emotion, customer issues are easier to handle compared with chats with negative or no emotion, and this is why employees respond faster to customers in such chats. To control for a possible task complexity factor that clearly varies between different chats, we controlled for total chat duration—assuming that overall, longer chats have more technical complexity than shorter chats. Indeed, we see that when keeping everything else equal, longer chats are associated with higher mean employee RT ($\gamma = 0.58$, $p<0.001$; see Table 3) suggesting that longer chats are more complex for employees to handle. Second, since all variables are aggregated to the chat level of analysis, it is not clear whether customer positive emotion caused employees to respond faster, or whether quick employee responses led to customer positive emotion. To support the direction of the customer emotion and employee behavior dynamic, a chronological distinction between independent and dependent variables is needed and will be addressed in Study 2. Thus Study 2 is intended to solidify the causality regarding the customer-emotion-employee-behavior dynamics that our predictions suggested.

Another limitation of Study 1 is that it does not take into account factors in other concurrent chats that the same employee is handling. That is, when an employee interacts with a customer (a focal chat), it is reasonable to assume that what happens in other concurrent chats, of the same employee, impacts his or her behavior, and especially employee RT in a focal chat. When these factors are considered, the employee RT could be broken down into two distinct variables. The first is “Other Time” (OT) which is the time the employee spends dealing with other concurrent customers. The second is the focal customer’s “Service Time” (ST), which is the net-time it takes the employee to process and respond to the focal customer messages in a given time interval. Our operational definition of Service Time ST is then:

Equation 2:

$$ST_{i,j} = RT_{i,j} - OT_{i,j}$$

Let $ST_{i,j}$ denote the service time of employee i to customer j. The separation of the employee RT into those two variables allows us to examine the effects of customer behavior on employee ST—which is a less "noisy" measure than employee RT. This division also allows us to record other features from parallel chats, such as the number of words an employee reads and writes in these chats. This allows for a more comprehensive modelling of employee behavior. The explicit definition of how to calculate ST and OT is illustrated in Figure 7 and will be addressed in Section 4.1.2.

An additional limitation of Study 1 is the simplistic treatment of emotion, which reduced each chat to one dominant emotion. That is, chats were classified as having either positive, negative or mixed emotion, according to the emotion that was dominant in the chat (when positive and negative emotion appeared at the same level, they were classified as mixed). This means we missed some of the variance of emotion in chats. In Study 2 we refine our analyses to include emotion variation that was not captured in Study 1.

4. Study 2

The main purpose of Study 2 is to explore the causal nature of the effects found in Study 1. In other words, we seek to understand whether customer emotion influences employee RT to a focal customer. Employee RT is comprised of both Service Time (ST) and Other Time (OT; see Equation 2) thus adding some variance that is not attributed to a focal customer but to other customers. In this study, we focus on ST while controlling for OT in order to draw refined conclusions about the net time it takes an employee to process and respond to the customer message as a function of customer emotion. Another possibility, however, is that employee ST impacts customer emotion; hence we will also examine this direction. Study 2 reports on a within-chat analysis, with chats separated into T_1 and T_2, and testing factors from T_1 as predictors of employee ST at T_2.

Seeking additional support for the results of Study 1, we will again test the following hypotheses:

Hypothesis 1:
Increase in customer positive emotion at T_1 *will* <u>*decrease*</u> *employee ST at* T_2*.*

Hypothesis 2:
Increase in customer negative emotion at T_1 *will* <u>*increase*</u> *employee ST at* T_2

Hypothesis 3:
Increase in customer mixed emotion at T_1 *will* <u>*decrease*</u> *employee ST at* T_2*.*

Hypothesis 4:
Customer positive emotion at T_1 *will moderate the impact that workload at* T_1 *has on employee ST at* T_2*.*

A reverse causality of the emotion-behavior effects that we predict should also be examined, to rule out the possibility that customer emotion (positive, negative or mixed) is induced by employee ST. The following hypothesis is presented to examine this:

Hypothesis 5:
Employee ST at T_1 *influences customer (a) positive emotion and (b) negative emotion at* T_2*.*

4.1 Method

Sampling and Data

To conduct the Study 2 tests, we defined a portion of each chat as T_1, and a subsequent portion as T_2. Prior work has shown that when predicting customer service employee behavior in written communications, the optimal number of messages to be used is 4 (Herzig et al., 2016). Therefore, we used 4 customer messages for T_1. The number of (employee) messages used for T_2 (where our dependent variable, employee ST, was measured) was 2, to increase the reliability of the measure. Using only 1 message was deemed unreliable since sometimes employees send a few messages in a row. Using more than 2 employee messages might also be less reliable; the timespan between each pair of employee messages is nearly a minute on average. A sample of too many employee messages at T_2 might result in a wide timespan where the immediate effect of customer emotion on employee behavior might dissolve. Hence we are bounded to sample the minimal number of employee messages possible.

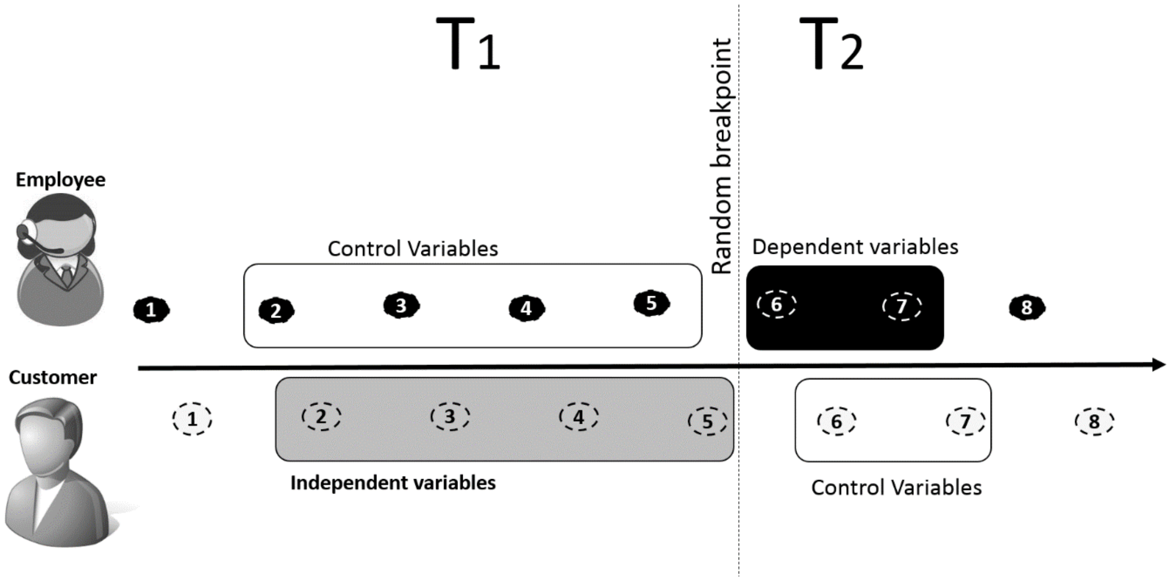

Figure 6 - The data sampling process: Black circles above and below the horizontal arrow represent employee and customer messages (respectively) in focal chats (16 messages total). IV's were collected from the 4 messages prior to the random breakpoint (marked with a grey rectangle at T_1. DV's were collected after the random breakpoint (from the black rectangle at T_2, and the parallel messages sent by the other interaction party over the duration of the time interval of T1 and T2 (marked with clear rectangles at T_1 and T_2) are used for recording control variables.

This definition of the sample caused a substantial reduction in our sample, since all chats with less than 4 customer messages (for T_1) and less than 2 subsequent employee messages (for T_2) were excluded. Therefore, a larger data set was obtained comprised of 20,355 chats conducted between January 1st and February 1st, 2016 of the same airline company as in Study 1. The effective sample for Study 2 included 5,999 chats. The chats lasted an average of 18 minutes and 32 seconds (SD=11 minutes and 26 seconds), and included an average number of customer messages of 5.16. As depicted in Figure 5, we randomly sampled a point in each chat[e], from which employee and customer messages were selected.

Variables

Variables are averages for each time period (T_1 or T_2) and hence appear twice accordingly (e.g., mean employee ST is calculated once for T_1 and once for T_2).

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[e] For the shortest chats in the data, the breakpoint was fixed and it was after the 4th customer message.

Dependent Variable - Employee Service Time

Employee RT was broken-down into two different variables:

1. Employee *Service Time* (ST) is the time it takes an employee to process and respond to focal customer messages.
2. Employee *Other Time* (OT) is the time an employee spends in other chats, at a selected time period.

In order to do so, we laid out a set of rules and assumptions;

(a) Employee Response Time (RT) is the time interval between $Customer_i$ message and $employee_j$ response to that message (see Figure 7, case A).

(b) If within a similar time interval, $employee_j$ sends a message to $Customer_{i+1}$, then $RT_{employeej}$ is divided into $ST_{employee\ j}$ and $OT_{employee\ j}$ (see Equation 2) using $employee_j$'s message to $Customer_{i+1}$ as a breakpoint (see Figure 7, case B).

(c) If within a similar time interval, $employee_j$ receives a message from $Customer_{i+1}$, then $RT_{employee\ j} = ST_{employee\ j}$ and $OT_{employee\ j}=0$ (see Figure 7, case C).

After this process, the DV – employee ST at T_2 (ST T_2) was computed by averaging employee ST in the messages sent at T_2 (M=40.74, SD=31.28, range 0.5 to 365.5 seconds; see Table 5).

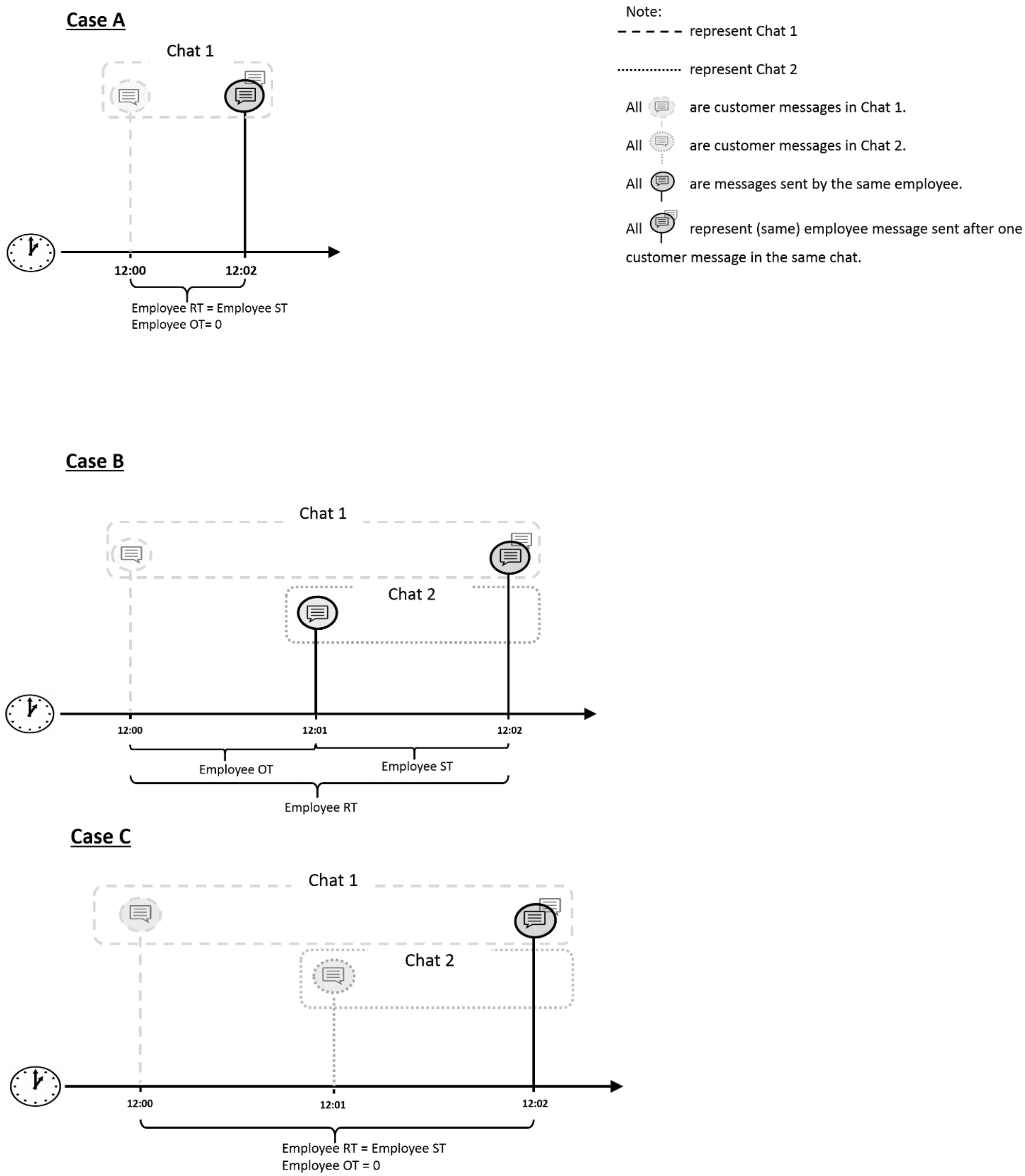

Figure 7 - Policies for splitting employee RT into employee ST and employee OT.

Independent Variables

(a) Customer Emotion:

Two emotion scores are calculated for each selected time period as follows:

Equation 3:

$$Pos_{i,j} = \frac{sum(EmoInt_{i,j}|EmotionVal_{i,j} = Positive)}{count(Nmessages_{i,j})}$$

Equation 4:

$$Neg_{i,j} = \frac{sum(EmoInt_{i,j}|EmotionVal_{i,j} = Negative)}{count(Nmessages_{i,j})}$$

Let $EmoIn_{i,j}$ denote emotion intensity, $EmotionVal_{i,j}$ denote emotion valence (positive or negative) and $Nmessages_{i,j}$ denote the number of customer messages in chat i, time period j.

(b) Mean number of customer words at T_1 ("McustWords T_1"; M=,17.63 SD=11.31, range 1 to 192.5; see Table 5)

Control Variables:

(a) Employee ID (Total of 44 employees).

(b) Day of week (70.36% weekdays and 29.64% weekends).

(c) Time of the day (28.71% morning, 25.32% noon and 45.97% evening).

(d) Type of service (54.21% sales and 45.79% customer service).

(e) Time customer waited before chat ("Queue"; M= 53.29, SD=121.73; range 0 to 1,956 seconds; see Table 5).

(f) Chat duration ("ChatD"; M=1,112.38 , SD=685.94, range 154 to 10,099 seconds; see Table 5).

(g) Mean number of employee words at T_1 ("MempWords T_1"; M=15.45, SD=23.51, range 1 to 254.75; see Table 5).

(h) Mean customer[f] response time at T_1 ("Customer RT T_1"; M=54.44, SD=34.45, range 1.50 to 664.50; see Table 5).

(i) Other words read T_1—defined as the average number of words employee received in parallel chats at T_1 ("OWR T_1"; M=7.85, SD=10.54, range 0 to 126.5; see Table 5).

(j) Other words written T_1—defined as the average number of words employee wrote in parallel chats at T_1 ("OWW T_1"; M=14.69 , SD=26.94, range 0 to 210; see Table 5).

(k) Time employees spend in other concurrent chats at T_1 ("OT T_1"; M=25.83, SD=15.35, range 3 to 201 seconds; see Table 5).

(l) Mean employee service time at T_1 ("ST T_1"; M=38.26, SD=23.82, range 1 to 311 seconds).

(m) Mean number of employee words at T_2 ("MempWords T_2"; M=26.77, SD=18.91, range from 2 to 282; see Table 5).

(n) Mean customer response time at T_2—only focal customers are considered here ("Customer RT T_2"; M=53.29, SD=51.90, range from 0 to 1,381; see Table 5).

(o) Mean number of customer words at T_2 ("McustWords T_2"; M=12.19, SD=10.17, range from 1 to 150; see Table 5).

(p) Other words read T_2—defined as the average number of words employee received in parallel chats at T_2 ("OWW T_2"; M=8.06, SD=14.68, range 0 to 286; see Table 5).

(q) Other words written T_2—defined as the average number of words employee wrote in parallel chats at T_2 ("OWW T_2"; M=16.40, SD=26.94, range 0 to 614; see Table 5).

(r) Time employees spend in other concurrent chats at T_2 ("OT T_2"; M=18.55, SD=39.8, range 0 to 936.5 seconds; see Table 5).

Statistical Analysis

The statistical method used in this study is Hierarchical Linear Model (HLM) using R (2014), and the 'lme4' (Bates et al., 2015) and 'lmerTsts' (Kuznetsova et al., 2016) packages.

[f] Only focal customers are taken into account when calculating mean customer RT.

4.2 Results

Descriptive Statistics

Correlations, means and standard deviations are shown in Table 5. All non-categorical variables were Box-Cox transformed[g] as recommended in linear models where residuals are not normally distributed (cf., Hyndman & Grunwald, 2000; see Table 6 for descriptive statistics and correlations of transformed variables).

[g] A method of log transformation which allows one to keep zero values.

Table 5 - Means, standard deviations, and correlations among variables.

Variable	*Mean*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. ChatD	1112.38	685.94																			
2. Queue	53.29	121.73	.00																		
3. ST T_1	38.26	23.82	.25**	.08**																	
4. ST T_2	40.74	31.28	.20**	.05**	.23**																
5. MempW T_1	15.45	23.51	.20**	-.00	.07**	.08**															
6. MempW T_2	26.77	18.91	.06**	-.01	.05**	.32**	.01														
7. OT T_1	25.83	15.35	.08**	.04**	.32**	.06**	.08**	.23**													
8. OT T_2	18.55	39.80	.17**	-.00	.01	.09**	.12**	.11**	.00												
9. OWR T_1	7.85	10.54	.11**	-.00	.14**	.06**	.55**	.01	.11**	.13**											
10. OWR T_2	8.06	14.68	.10**	-.00	-.02	.14**	.12**	.08**	.00	.55**	.14**										
11. OWW T_1	14.69	19.08	.10**	-.00	.03*	.03*	.69**	.01	.07**	.09**	.50**	.12**									
12. OWW T_2	16.40	26.94	.12**	-.02	-.02	.05**	.13**	.08**	.01	.73**	.18**	.50**	.14**								
13. CustRT T_1	54.44	34.45	.35**	.02	.26**	.16**	.19**	.03*	.16**	.07**	.16**	.05**	.13**	.06**							
14. CustRT T_2	53.29	51.90	.30**	.00	.11**	.16**	.07**	.08**	.02	.10**	.05**	.09**	.03*	.10**	.21**						
15. McustW T_1	17.63	11.31	.11**	.06**	.21**	.10**	.09**	.24**	.40**	.01	.11**	.02	.06**	.00	.31**	.05**					
16. McustW T_2	12.19	10.17	.16**	-.00	.09**	.20**	.05**	.28**	.17**	.07**	.05**	.09**	.04**	.05**	.12**	.25**	.34**				
17. Pos T_1	0.18	0.35	-.02	-.04**	.01	-.06**	-.01	.03*	.06**	-.03**	.00	-.04**	-.02	-.02	-.05**	-.04**	.06**	.00			
18. Pos T_2	0.23	0.41	-.06**	.00	.01	-.05**	.03*	-.02	.03*	.00	.02	-.01	.03*	-.01	-.01	-.05**	.04**	.01	.10**		
19. Neg T_1	0.11	0.25	.05**	.02	.03**	.06**	.01	.07**	.05**	.03*	.02	.02	.01	.01	.07**	.02	.14**	.07**	-.12**	-.04**	
20. Neg T_2	0.06	0.20	.05**	.00	.01	.06**	-.00	.06**	.02	.04**	-.00	.06**	-.01	.02	.01	.04**	.05**	.20**	-.03*	-.11**	.09*

Note. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 6 - Means, standard deviations, and correlations among transformed variables.

Variable	*Mean*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. ChatD	6.86	0.55																			
2. Queue	2.01	1.93	.00																		
3. ST T_1	3.51	0.59	.32**	.07**																	
4. ST T_2	3.48	0.75	.25**	.03*	.20**																
5. MempW T_1	1.80	1.52	.20**	.00	.08**	.04**															
6. MempW T_2	3.13	0.63	.07**	-.02	.03*	.38**	-.01														
7. OT T_1	3.16	0.51	.11**	.05**	.40**	.07**	.08**	.16**													
8. OT T_2	1.58	1.70	.15**	-.01	-.01	.06**	.19**	.09**	.02												
9. OWR T_1	1.48	1.25	.15**	-.01	.18**	.05**	.57**	.01	.13**	.25**											
10. OWR T_2	1.24	1.37	.11**	-.01	-.05**	.21**	.17**	.12**	.00	.54**	.20**										
11. OWW T_1	1.88	1.48	.15**	.00	.06**	.02	.88**	-.01	.07**	.19**	.54**	.17**									
12. OWW T_2	1.65	1.68	.12**	-.02	-.03*	.04**	.20**	.07**	.02	.90**	.27**	.49**	.21**								
13. CustRT T_1	3.86	0.57	.43**	.02	.33**	.19**	.22**	.04**	.23**	.08**	.19**	.05**	.18**	.08**							
14. CustRT T_2	3.70	0.77	.37**	.02	.14**	.28**	.09**	.15**	.03*	.15**	.10**	.15**	.08**	.14**	.29**						
15. McustW T_1	2.78	0.52	.11**	.04**	.21**	.14**	.07**	.18**	.34**	.03*	.12**	.04**	.06**	.02	.38**	.09**					
16. McustW T_2	2.35	0.67	.21**	-.00	.08**	.25**	.04**	.24**	.12**	.10**	.06**	.13**	.04**	.09**	.12**	.40**	.32**				
17. Pos T_1	0.14	0.22	-.06**	-.05**	-.02	-.09**	-.03**	.02	.04**	-.04**	-.02	-.04**	-.04**	-.02	-.07**	-.07**	.07**	.01			
18. Pos T_2	0.16	0.26	-.09**	.00	.02	-.06**	.01	-.03*	.03*	-.01	.02	-.02	.02	-.01	-.02	-.10**	.06**	.03*	.11**		
19. Neg T_1	0.09	0.17	.05**	.02	.01	.05**	.00	.06**	.03*	.02	.01	.02	-.01	.02	.04**	.04**	.14**	.08**	-.15**	-.05**	
20. Neg T_2	0.05	0.14	.06**	.00	.01	.07**	-.01	.06**	.02	.01	.01	.04**	-.01	.00	.02	.06**	.05**	.19**	-.03*	-.13**	.10**

Note. * $p < .05$; ** $p < .01$; *** $p<.001$. All variables are Box-Cox transformed.

Hypotheses Testing

To decide which type of model fits best to our analysis; Ordinary Least Square (OLS) or Hierarchical Linear (HLM) Model, we calculated the Intraclass Correlation (ICC) between any two measurements of the dependent variable for the same employee. Results reveal a weak yet significant correlation (ICC=0.095, Wald Z=3.78, p<0.001) indicating that 9.5% of the variance in employee RT can be explained by employee ID alone. Hence, all hypotheses in this study are tested using an HLM approach, which accounts for the random effect employees have on the dependent variable, as each conversation is nested within an employee. All hypotheses were tested using the following model:

Equation 5:

$$log1p\left(ST_{i,j}^{T_2}\right) = \gamma_0 + u_i + \gamma_1 x_{i,j} + \gamma_2 log1p(Pos_{i,j}^{T_1}) + \gamma_3 log1p\left(Neg_{i,j}^{T_1}\right) + \gamma_4 log1p\left(McustW_{i,j}^{T_1}\right) + \gamma_5 log1p\left(McustW_{i,j}^{T_1}\right) \cdot log1p(Pos_{i,j}^{T_1}) + \gamma_6 log1p\left(McustW_{T_{1_{i,j}}}\right) \cdot log1p\left(Neg_{i,j}^{T_1}\right) + \varepsilon_{i,j}$$

u_i is the unique addition of each employee i to the intercept γ_0; $x_{i,j}$ includes control variables as listed in the Variables in Section 4.1. $Pos_{\ i,j}$ and $Neg_{\ i,j}$ denote customer positive or negative emotion towards employee i at chat j.

Results are presented in Table 7. AIC value is the lowest for the full model (see Table 7), suggesting that the full model has a better fit to the data compared with the null and reduced model. Contrary to Study 1, we found a negative relationship between customer positive emotion at T_1 and employee ST at T_2 (γ= -0.78, p<0.001). This effect is beyond the effects of all other control variables, <u>including customer positive emotion at T_2</u> (γ= -0.91, p<0.01) thus supporting Hypothesis 1 and suggesting a causal effect of customer positive emotion on employee ST in a focal chat. In addition, contrary to the prediction of Hypothesis 2, an increase in customer negative emotion at T_1 had no significant effect on employee ST at T_2 (γ= -0.29, p>0.05). Hypothesis 3, which predicted that mixed emotion facilitates employee performance, was not supported (no effect of Positive T_1 and Negative T_1 interaction on employee RT (γ= 0.33, p>0.05).

Hypothesis 4, which predicted a moderation effect of customer positive emotion on the impact of workload on employee ST, was supported. Indeed, the effect of McustWords X positive emotion (both at T_1) was significant (γ=0.21, p<0.01). Further simple slopes analysis revealed that in chats with no positive emotion at T_1, employee ST remained the same regardless of the number of customer words at T_1. However, when customer expressed higher positive emotion at T_1, and customer number of words at T_1 was low, employee ST at T_2 was shorter. In contrast, employee ST is higher at T_2 when customers express high levels of positive emotion <u>and</u> write more words at T_1 (see Figure 8) suggesting that exposure to customers who express high levels of positive emotion <u>and</u> pose higher demands (as employees are requested to read more) leads employees to respond slower.

Table 7 - Hierarchical Linear Modeling (HLM) Result Testing Hypotheses 1, 2, 3 and 4.

			DV = employee ST at T_2			
	Null model		Reduced model		Full model	
	γ	*SE*	γ	*SE*	γ	*SE*
Intercept	3.55***	0.04	0.46***	0.13	0.57***	0.14
Variance Components						
Within-group variance (Level 1)	0.51	-	-	-	-	-
Between-group variance (Level 2)	0.05	-	-	-	-	-
Control Variables						
MempWords T_1			0.01***	0.01	0.01	0.01
MempWords T_2			0.37***	0.01	0.37***	0.01
Customer RT T_1			0.07***	0.02	0.07***	0.02
Customer RT T_2			0.09***	0.01	0.09***	0.01
ST T_1			0.13***	0.01	0.13***	0.02
OT T_1			-0.09***	0.02	-0.09***	0.02
OT T_2			-0.06***	0.01	-0.06***	0.01
OWR T_1			-0.16†	0.01	-0.02†	0.01
OWR T_2			0.11***	0.01	0.11***	0.01

OWW T_1		-0.01	0.01	-0.01	0.01
OWW T_2		0.01	0.01	0.01	0.01
McustWords T_2		0.11***	0.01	0.11***	0.14
Queue		0.01	0.01	0.01	0.01
Type of Service: Sales[(a)]		-0.03	0.06	-0.03	0.06
ChatD		0.13***	0.02	0.13***	0.02
Time of day (Morning)[(b)]		-0.01	0.02	-0.03	0.02
Time of day (noon)		-0.01	0.02	-0.01	0.02
Day of week[(c)]		-0.13	0.02	-0.01	0.02
Independent Variables					
Positive emotion T_1		-0.21***	0.04	-0.78***	0.20
Positive emotion T_2		-0.09***	0.03	-0.91**	0.03
Negative emotion T_1		-0.01	0.05	-0.29	0.26
Negative emotion T_2		0.03	0.06	0.03	0.06
McustWords T_1		0.01	0.02	-0.03	0.02
McustWords X PosT_1				0.21**	0.07
McustWords X NegT_1				0.10	0.09
PosT_1 X NegT_1				-0.33	0.34
-2 log likelihood	13,119.8	11,374		11,363.8	
AIC	13,125.9	12,932.8		11,421.8	
Pseudo-R^{2}[(d)]		27.61%		27.89%	

Note. [(a)]Two types of employee work, where 1=Service, 0=Sales. [(b)]Compared with evening. [(c)]Weekdays compared with weekends. [(d)]Pseudo-R^2 was calculated using the formula suggested by Snijders & Bosker (2012). ***$p<0.001$, **$p<0.01$, *$p<0.05$, †$p<0.1$

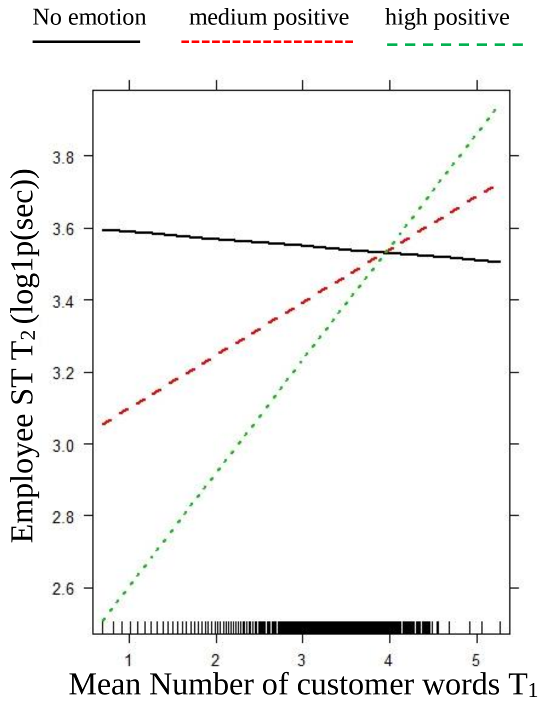

Figure 8 - Simple slopes of Number of Customer Words X positive emotion interaction. Variables on the Y and X axes are log1p() transformed.

Examining the Effects of Employee RT on Customer Emotion (Hypothesis 5)

The results we have presented so far support the notion that customer emotion impact employee behavior—namely, speed of process and response to customers' requests in focal chat. However, it is also plausible that employee behavior impacts customer emotion. To better understand the direction of the customer emotion-employee behavior relationship, we switched between the main IV with the DV. That is, we examined the effects of employee ST at T_1 on customer emotion at T_2. To examine this direction of behavior-emotion effects while remaining consistent with the sampling process introduced above, we sampled the data again so that T_1 includes two employee messages, from which employee behavior is recorded, and T_2 includes 4 customer messages, from which customer emotion is recorded. This sampling resulted in a sample size of 3,297.

Two models were estimated to examine the effects of employee behavior on customer emotion—one for positive and one for negative emotion:

Equation 6:

$$log1p\left(Pos_{i,j}^{T_2}\right) = \gamma_0 + u_i + \gamma_1 x_{i,j} + \gamma_3 log1p\left(ST_{i,j}^{T_1}\right) + \varepsilon_{i,j}$$

Equation 7:

$$log1p(Neg_{i,j}^{T_2}) = \gamma_0 + u_i + \gamma_1 x_{i,j} + \gamma_3 log1p\left(ST_{i,j}^{T_1}\right) + \varepsilon_{i,j}$$

α_i is the unique addition of each employee i to the intercept γ_0 and $x_{i,j}$ denotes all the independent and control variables mentioned in Section 4.1.2.

As shown in Table 8, employee ST at T_1 is positively related to customer positive emotion at T_2 (γ=0.04, p<0.001). Also, no significant relationship between employee ST at T_1 and customer negative emotion at T_2 was found (γ=0.01, p>0.05); see Table 9. Therefore, Hypothesis 5 is partly supported.

Table 8 - Hierarchical Linear Modeling (HLM) Result Testing Hypothesis 5a.

	DV = Positive emotion T_2			
	Null model		Full model	
	γ	*SE*	γ	*SE*
Intercept	0.20***	0.01	0.42***	0.07
Variance Components				
Within-group variance (Level 1)	0.07	-	-	-
Between-group variance (Level 2)	0.01	-	-	-
Control Variables				
Mean employee words T_1			-0.01	0.01
Mean employee words T_2			0.02	0.01
Customer mean RT T_1			0.01	0.01
Customer mean RT T_2			-0.05***	0.01
Customer mean number of words T_2			0.06***	0.01
Employee ST T_2			0.03**	0.01
Positive emotion T_1			0.11***	0.02
Negative emotion T_1			-0.04	0.03
Negative emotion T_2			-0.29***	0.03

Customer mean number of words T_1			0.01	0.01
Employee OT T_1			0.01	0.01
Employee OT T_2			0.01	0.01
OWR T_1			0.01	0.01
OWR T_2			0.01	0.01
OWW T_1			0.01	0.01
OWW T_2			-0.01	0.01
Queue time (prior to chat)			-0.01**	0.01
Type of Service: Sales[a]			-0.01	0.01
Chat length			-0.03**	0.01
Time of day (Morning)[b]			0.01	0.01
Time of day (Noon)			0.01	0.01
Day of week[c]			0.01	0.01
Independent Variable				
Employee ST T_1			0.04***	0.01
-2 log likelihood	756.2		525.4	
AIC	762.3		577.4	
Pseudo-R^{2}[d]			6.72%	

Note. [a]Two types of employee work, where 1=Service, 0=Sales. [b]Compared with evening. [c]Weekdays compared with weekends. [d]Pseudo-R^2 was calculated using the formula suggested by Snijders & Bosker (2012). ***p<0.001, **p<0.01, *p<0.05, †p<0.1

Table 9 - Hierarchical Linear Modeling (HLM) Result Testing Hypothesis 5b.

	DV = Negative emotion T_2			
	Null model		Full model	
	γ	*SE*	γ	*SE*
Intercept	0.07***	0.01	-0.09*	0.04
Variance Components				
Within-group variance (Level 1)	0.02	-	-	-
Between-group variance (Level 2)	0.01	-	-	-
Control Variables				

Mean employee words T_1		-0.01	0.01
Mean employee words T_2		0.02***	0.01
Customer mean RT T_1		0.01	0.01
Customer mean RT T_2		0.02***	0.01
Customer mean number of words T_2		0.07***	0.01
Positive emotion T_1		-0.01	0.01
Negative emotion T_1		0.09***	0.02
Positive emotion T_2		-0.09***	0.01
Customer mean number of words T_1		0.01	0.01
Employee ST T_2		0.01	0.01
Employee OT T_1		0.01	0.01
Employee OT T_2		0.01	0.01
OWR T_1		0.01	0.01
OWR T_2		0.01†	0.01
OWW T_1		-0.01	0.01
OWW T_2		0.01	0.01
Queue time (prior to chat)		0.01	0.01
Type of Service: Sales[(a)]		0.01	0.01
Chat length		0.01	0.01
Time of day (Morning)[(b)]		-0.01	0.01
Time of day (Noon)		-0.01	0.01
Day of week[(c)]		0.01*	0.01
Independent Variable			
Employee ST T_1		0.01	0.01
-2 log likelihood	-2825.8	-3179.6	
AIC	-2819.9	-3127.6	
Pseudo-$R^{2(d)}$		10.26%	

Note. [(a)]Two types of employee work, where 1=Service, 0=Sales. [(b)]Compared with evening. [(c)]Weekdays compared with weekends. [(d)]Pseudo-R^2 was calculated using the formula suggested by Snijders & Bosker (2012). ***p<0.001, **p<0.01, *p<0.05, †p<0.1

5. General Discussion

The current research analyzed two large data sets of a western airline company customer contact center. The natural interactions recorded on these data and analyzed by a sentiment analysis engine revealed some interesting effects of customer emotion on employee behavior in chats—an increasingly growing service channel (Messina, 2016). Each section in the discussion will refer to effects of each type of emotion explored in the current work (positive, negative and mixed emotion) and will combine results of both Study 1 and Study 2.

5.1 Effects of Positive Customer Emotion on Employee Service Time

Our analyses generally support the notion that customer positive emotion reduces employee Response Time (RT). This is true even when we exclude the time employees spend with other customers from employee RT, leaving a more accurate measure of employee Service Time (ST; see Equation 2). Throughout both studies, our results generally support the Broaden and Build Theory (BBT; Vacharkulksemsuk & Fredrickson, 2013) that advocates for the cognitive enhancement and benefits of positive emotion on individuals.

Our results also show that emotion intensity must be considered in this effect, as the effect of positive emotion described above has a boundary condition. In Study 1 we showed that an increase in customer positive emotion is related to longer delays in service (see Figure 4). That is, customers who expressed higher levels of positive emotion eventually received slower service compared with customers who expressed mild positive emotion. Study 2 further supports this notion by showing that when over-demanding customers also express high positive emotion, the service they received was slower even compared with customers who express no emotion (see Figure 8). That is, when customers wrote a lot of words and expressed high levels of positive emotion, they received slower service. Such a non-adaptive impact of positive emotion was documented previously (see Davis, 2009 for a meta-analysis) and led researchers to suggest that the effects of positive emotion are not linear (Grant & Schwartz, 2011). However, we conducted additional analyses and did not find any non-linear effects of customer positive emotion in the current research.

In the context of the current work, the non-adaptive impact of intense positive and negative emotion of customers on employee performance supports the notion that employees' cognitive resources are reduced as a result of exposure to customer emotion—regardless of emotion valence—thus supporting the Affective Event Theory (Weiss & Cropanzano, 1996) in this case.

In terms of Regulatory Focus theory (Higgins, 1997, 1998), it seems that employees were in a *promotion* mindset. That is, they were motivated to return to customers who expressed positive emotion; hence employee RT and ST were shorter for such customers. However, since we did not measure promotion or prevention focus in the current research, it is not clear whether employees were indeed promotion focused and this question remains for future work.

A possible alternative explanation for reduced ST that is evoked after employee exposure to customer positive emotion is that employees put less effort processing customer requests. Employees might interpret customer positive emotion as a sign indicating that customers are satisfied with the service process, leading them to invest less effort and generate faster responses. To rule out this explanation, future research should also account for quality of employee responses. The challenge here would be to find a way to automatically rank the quality of employee responses. One way to do so could be to measure typos and grammar mistakes in employee messages.

5.2 Effects of Negative Emotion on Employee Service Time

In the case of negative customer emotion, we were able to find significant effects only in Study 1. One possible explanation for non-significant effects of negative customer emotion in Study 2 could be that our sampling method reduced our sample size substantially, leaving only long chats. Future work should examine the effects of customer negative emotion in shorter chats as well.

Results of Study 1 showed that only when customer negative emotion is high, employee service time increases significantly. In most cases where customers express mild negative emotion, there is no change in employee ST or RT compared with customers who express no emotion. However, if we change the reference point to customers who express positive emotion, increases in employee ST and RT are evident (see Table 4). This finding could be explained by both types of approaches used in the current research—cognition and motivation.

AET (Weiss & Cropanzano, 1996) suggests that the reason for the increase in employee ST and RT is due to the increased cognitive load that customer negative emotion induced; Regulatory Focus Theory (Higgins, 1997, 1998) suggests that employees are motivated to avoid such customers (prevention focus). Such avoidance can be manifested in three different ways: employees could (1) respond slower to customers expressing negative emotion, (2) increase the time they spend with other customers and (3) respond to customers in an emotion-dependent order. That is, if an employee interacts with one customer who expresses negative emotion and two customers who express no emotion, would the employee answer customers in a First-In-First-Out (FIFO) fashion, or will this order be disrupted? Also, if the order is not FIFO, what would it be? Future research should consider the avoidance behavior described above to give us a deeper understanding of employee regulatory focus in chat service.

5.3 Effects of Customer Mixed Emotion on Employee Service Time

The effects of mixed emotion in the current work were inconsistent. First, we saw that when customers express mixed emotion, the service they were provided with was faster relative to customers who didn’t express any emotion. However, when we introduced some changes in the sampling process and operationalized the measure of mixed emotion differently in Study 2, we found no effects of mixed emotion on employee ST.

Mixed emotion is a contrast of two conflicting emotions (i.e., positive and negative), a fact that by itself could draw employee attention. In Study 1, our DV (employee RT) included both employee ST and the time employees spent in other concurrent chats (employee OT). Thus, employee RT partly represents employee attention, since low employee OT means that employees spend less time in other chats. It is possible that the significant effects found in Study 1 were due to the variance added from employee OT. Hence, the question whether employees in Study 2 paid more or less attention to customers who expressed mixed emotion remains. Future research should examine employee ST and OT as DVs to examine the effects of customer mixed emotion on employee attention.

5.4 The Cycle of Customer Emotion and Employee Behavior

Surprisingly, we found that employee ST led to customer positive emotion and not to negative emotion, as one would expect. One possible explanation could be that this relationship is confounded with the quality of employee responses. Future research should find a metric of the quality of employee messages or consider a different measure of employee behavior that will not be confounded in this manner.

In the current research we examined only direct effects of customer emotion and employee behavior (in both directions). However, such a dynamic is likely to have a cycle-like relationship (Hareli & Rafaeli, 2008) where behaviors and emotions of both interaction parties influence each other (directly and indirectly) in a recursive manner. Therefore, it is necessary to examine models that consider indirect effects of emotion. Such a model should also consider emotion expressed by employees to allow a more comprehensive understanding of the emotion-behavior dynamic.

5.5 Limitations and Future Research

Other than the limitations mentioned above, it is important to note that the findings we presented here are based on data from one firm. Future research should examine the effects found here in multiple firms and industries to increase the external validity of the current research. In addition, we measured emotion based on its valence (positive or negative) rather than using measures of discrete emotions (e.g., anger, sadness, frustration etc.), which are likely to have different effects on employee behavior (c.f., Rupp & Spencer, 2006). Therefore, future research should consider using sentiment analysis tools that can distinguish between different types of emotion.

5.6 Implications

Our research suggests that customer positive emotion helps in facilitating employee performance in most cases. A service system that could measure customer emotion in real-time could route customers to employees based on customer emotion and by doing so, to increase service efficiency. Take the case of the routing policy in the firm we investigated in the current research, for example. It is based only on employee availability. Specifically, each employee has three “slots” and when at least one slot is available, a new customer is directed to that employee. We suggest that customer routing can consider customer-expressed emotion in this process and direct more customers to employees who are predicted to provide faster service (employees who are exposed to mild expressions of positive customer emotion). Another possibility is to direct fewer customers to employees who are predicted to provide slower service (employees who are exposed to high levels of positive or negative customer emotion). Such an adjustment will increase the efficiency of service systems and will insure a fairer division of labor among employees.

From a customer's point of view, it seems like the best strategy, in terms of emotion expression, is to express positive emotion towards employees, as it could reduce the duration of the service process in chat-based customer service.

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8. Appendix

Appendix A

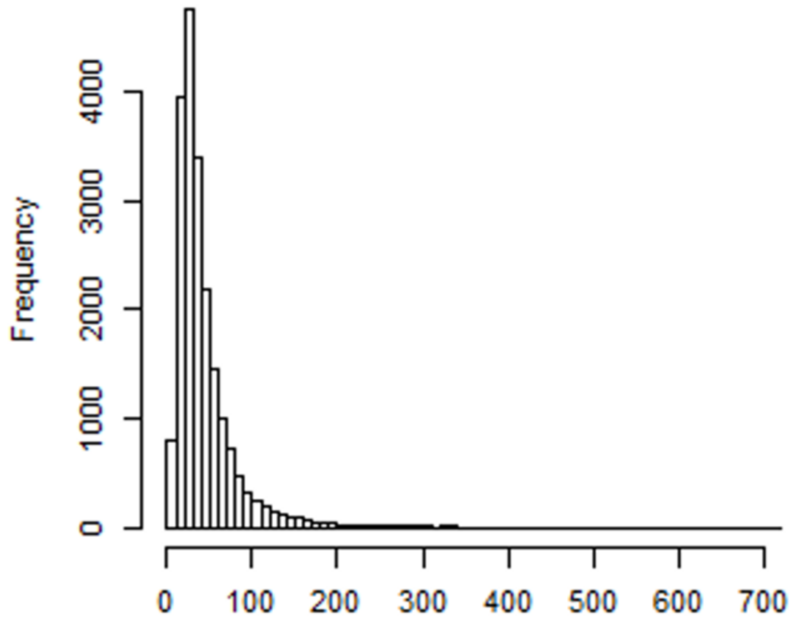

Figure 9 – Distribution of employee RT.

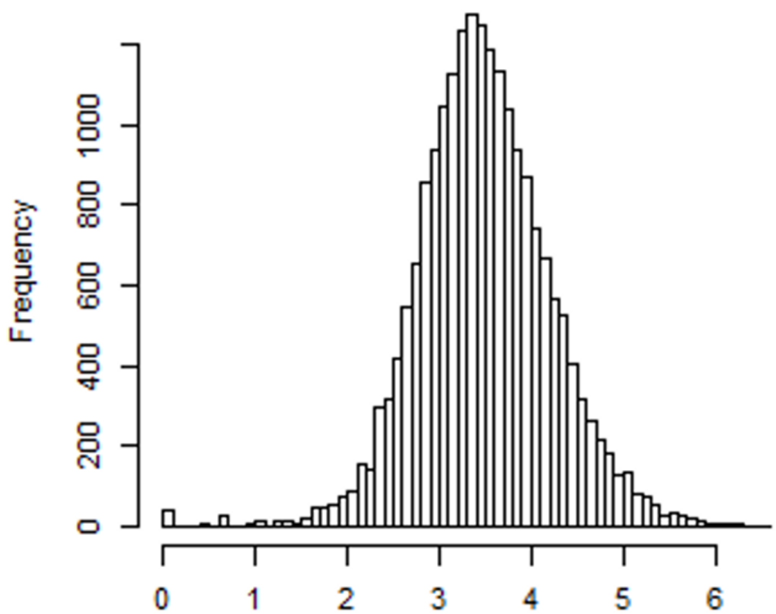

Figure 10 – Distribution of log1p(employee RT).

Appendix B

Table 10 - Hierarchical Linear Modeling (HLM) result testing all hypotheses of Study 1 using a subset of only chats where emotion was expressed by customers.

	DV = Employee RT					
	Null model		Reduced model		Full model	
	γ	*SE*	γ	*SE*	γ	*SE*
Intercept	3.95***	0.05	-0.58***	0.12	-0.61***	0.13
Variance Components						
Within-group variance (Level 1)	0.36					
Between-group variance (Level 2)	0.07					
Control Variables						
MempWords			0.45***	0.02	0.44***	0.02
Customer RT			-0.13***	0.02	-0.13***	0.02
Queue			-0.01	0.01	-0.01	0.01
Type of Service: Sales[(a)]			-0.10	0.02	-0.10	0.07
ChatD			0.47***	0.01	0.47***	0.01
Time of day (Morning)[(b)]			-0.04†	0.02	-0.04	0.02
Time of day (Noon)			0.03	0.02	0.03	0.02
Day of week[(c)]			-0.01	0.02	-0.01	0.02
Independent Variables						
Negative emotion[(d)]			0.16***	0.02	0.35***	0.11
Mixed emotion[(d)]			0.15	0.03	-0.13	0.21
EmoInt			0.47***	0.04	0.33***	0.05
McustWords			0.15***	0.02	0.19***	0.03
EmoInt X negative[(e)]					0.42***	0.10
EmoInt X mixed[(e)]					0.56*	0.10
McustWords X negative					-0.12**	0.04
McustWords X mixed					-0.02	0.08
-2 log likelihood	-3,858.3		-2,996.3		-2,983.2	
AIC	7,722.6		6,022.7		6004.4	
Pseudo-$R^{2(f)}$			36.35%		36.71%	

Note.[(a)]Two types of employee work, where 1=Service, 0=Sales. [(b)]Compared with evening. [(c)]Weekdays compared with weekends. [(d)]Compared with positive emotion. [(e)]Compared with Emotion intensity X positive emotion. [(f)]Pseudo-R^2 was calculated using the formula suggested by Snijders & Bosker (2012). ***p<0.001, **p<0.01, *p<0.05, †p<0.1

Appendix C

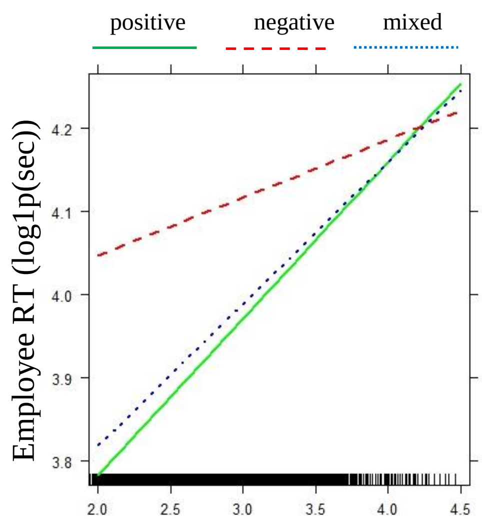

Figure 11 - Simple slopes of Number of Customer Words X emotion valence interactions using a subset of only chats where emotion was expressed by customers. *Variables on the Y and X axes are log1p() transformed.*

Appendix D

Table 11 - Coefficients representing difference in employee RT as a function of the dominant emotion expressed in chats interacting with emotion intensity. Coefficients are obtained by changing the reference group dummy coded as "0".

	1. EmoInt X positive (dummy code=0)	2. EmoInt X negative (dummy code=0)
1. EmoInt X positive (dummy code=1)	-	-
2. EmoInt X negative (dummy code=1)	0.42***	-
3 EmoInt X mixed (dummy code=1)	0.56*	0.14

בחלקו השני של המחקר, ביקשנו לבסס קשר סיבתי בין הרגשות המובעים על ידי לקוחות לבין זמני התגובה של נותני השירות. לשם כך, ניתחנו נתונים חדשים ותיעדנו את הרגש שהובע על ידי לקוחות ואת זמני התגובה של נותני השירות <u>לאחר</u> שנחשפו לרגש הלקוחות. בנוסף, ביקשנו לחדד את המשתנה התלוי (זמני התגובה של העובדים) על ידי הפחתה של הזמנים בהם נותני השירות טיפלו בפניות אחרות. כלומר, בחלק זה של המחקר, המשתנה התלוי הוא זמן השירות נטו ללקוח/ה מסויים/ת. נמצא כי עליה ברגש חיובי של לקוחות גרם בתורו <u>לירידה</u> בזמני התגובה של נותני השירות. בניגוד לחלקו הראשון של המחקר, לא נמצא קשר בין רגש שלילי של לקוחות לבין זמני התגובה של העובדים. השלכות פרקטיות וכיוונים למחקרי המשך מוצעים בסוף העבודה.

מתן שירות לקוחות הינו תהליך הכרוך באינטראקציה בין לקוחות לבין החברה. בימים אלו, חברות מציעות שירותים המועברים בערוצים שונים כמו למשל שירות פנים-מול-פנים, שירות טלפוני, שירות עצמי דרך אתר אינטרנט יעודי, שירות דרך רשתות חברתיות (כמו "פייסבוק") ועוד. תפעול מרכז שירות הינו הליך מורכב אשר מחייב מתן שירות איכותי תוך כדי שמירה על יעילות המרכז – שני כוחות שבאים האחד על חשבון השני. דו"ח של Forbs אשר מסכם את עלויות התפעול של החברות המספקות שירותים ללקוחות בארצות הברית חושף עלויות תפעול מפתיעות בהיקפן בסך כולל של כ 112 מיליארד דולר, אך המשאבים האלו מספיקים עבור מענה חלקי בלבד של כמחצית מתוך 270 מיליארד פניות בשנה (Upbin, 2013).

בניסיון להגדיל את יעילותם של מרכזי שירות, בחרנו לעסוק בחלק מרכזי בהליך השירות- האינטראקציה שבין לקוחות לנותני שירות. המחקר הנוכחי מנתח אלפי אינטראקציות שירות ומכירות אשר התקיימו בערוץ שירות ההולך והופך נפוץ בקרב חברות שירות - צ'ט חי עם נציג שירות. היתרון בביצוע מחקר על בסיס נתונים מסוג זה הוא שכל ההתנהגויות של העובדים והלקוחות במסגרת השירות מתועדות באופן אובייקטיבי, סמוי ומתמשך לאורך כל אינטראקציית השירות, ללא כל הפרעה לתהליך השירות. ערוץ שירות זה שונה בבסיסו משירות לקוחות הניתן בערוצים אחרים כמו שירות דרך טלפון או מרכזי שירות פיזיים. ההבדל העיקרי בין שירות דרך צ'ט לערוצי שירות אחרים הוא בכך שנותני השירות יכולים להעניק שירות למספר לקוחות במקביל כאשר ערוץ השירות הוא צ'ט, אך רק ללקוח/ה אחד/ת כאשר השירות ניתן בערוצי שירות "מסורתיים". עובדה זו הופכת את פלטפורמת השירות דרך צ'ט לקרקע פוריה למחקר התנהגותי מפני שלהתנהגויות העובדים בפלטפורמה זו יש <u>דרגות חופש רבות</u> יותר אשר מתועדות באופן מתמשך.

באינטראקציות שירות לקוחות מביעים לעיתים רגשות שונים. הרגשות המובעים עשויים לנבוע כתוצאה מהשירות או המוצר אותו החברה מוכרת, אך לא בהכרח. למשל, לקוח יכול להביע תסכול או כעס על כך ששירות האינטרנט בביתו איטי מהמובטח, לקוחה אחרת יכולה להביע שמחה ושביעות רצון מהשירות אותו היא מקבלת ברגע נתון ולקוח נוסף יכול להביע תסכול שנובע מחוויה אחרת בחייו שאינה קשורה בהכרח לשירות. נותני השירות קולטים רגשות אלו כמידע הקיים בסביבתם ומתאימים את התנהגותם בהתאם אליו.

במחקר הנוכחי השתמשנו בנתונים אשר התקבלו מחברת LivePerson Inc. (http://www.liveperson.com/), התמקדנו בזמני התגובה של נותני השירות להודעות אשר נשלחו על ידי לקוחות והתייחסנו לזמנים אלו כמדד לביצועי נותני השירות. התוצאות מראות כי נותני שירות מגיבים מהר יותר ללקוחות אשר מביעים מידה מתונה של רגש חיובי, אך נוטים להגיב לאט יותר כאשר לקוחות מביעים רגש שלילי או חיובי בעוצמה גבוהה. בנוסף, נמצא כי כאשר לקוחות הביעו רגש כלשהו (חיובי או שלילי) הקשר החיובי בין עומס עבודה לבין זמני התגובה של העובדים מתמתן. כלומר, הפגיעה בזמני השירות אשר נגרמת מעומס עבודה נמוכה יותר כאשר לקוחות הביעו רגש כלשהו.

המחקר נעשה בהנחייתן של פרופ׳ ענת רפאלי וד״ר גלית יום-טוב בפקולטה להנדסת תעשייה וניהול.

אני מודה לטכניון ולקרן גוטווירט על התמיכה הכספית הנדיבה בהשתלמותי.

מידול התגובה ההתנהגותית של עובדים לרגשות שהובעו על ידי לקוחות: בחינה סמויה של התנהגות נציגי שירות לקוחות

חיבור על מחקר

לשם מילוי חלקי של הדרישות לקבלת התואר מגיסטר למדעים ב מגיסטר למדעים במדעי ההתנהגות והניהול- פסיכולוגיה ארגונית (עם תזה)

דניאל אלטמן

הוגש לסנט הטכניון - מכון טכנולוגי לישראל

חשוון, תשע״ז אוקטובר 2016