Do Customer Emotions Affect Worker Speed? An Empirical Study of Emotional Load in Online Customer Contact Centers

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Problem Definition: Research in Operations Management has focused mainly on system-level load, ignoring the fact that service agents and customers express a variety of emotions that may impact service processes and outcomes. We introduce the concept of *emotional load*—the emotional demands that customer behaviors impose on service agents—to analyze how customer emotions affect service worker's behavior.

Academic / Practical Relevance: Theories in psychology literature generate ambiguous predictions about the effect of customer emotion on employee productivity: some theories predict that emotions expressed by customers reduce productivity (e.g. by increasing the service time required to serve an angry customer) whereas other theories predict a positive effect (e.g. by motivating the agent to finish an unpleasant conversation as quickly as possible). We aim to shed light on which theory is more dominant in reality and discuss practical opportunities that arise from measuring emotional load, and how it can be used to enhance productivity.

Methodology: We measure emotional load of agents using a sentiment analysis tool which measure positive/negative customer emotions in online chat-type contact center, and link it to agent behavior: response time, the extension of messages and the number of messages required to complete a service request. Identifying a causal effect of customer emotion on agent behavior using observational data is challenging because there are confounding factors associated to the complexity of service requests, which are related to both emotions and agent behavior. Our identification strategy uses panel data exploiting the variation across messages within a focal request, using fixed effects to control for unobserved factors associated to case complexity. Instrumental variables are also used to address issues of measurement error and other endogeneity problems; the instruments are based on exogenous shocks to agent productivity that have been studied in the service operations literature.

Results: Analyses show that emotional load created by negative customer emotions increases agent response time, the extension of the agent messages (a measure of effort) and the required number of messages needed to solve a case. Emotional load and agent RT reciprocally effect each other, with long agent response times and high number of messages producing more negative customer emotions.

Managerial Implications: The emotional content in customer communications is an important factor of the workload assigned to agents in a service system. Our study provides a rigorous methodology to measure the emotional content from customer text messages and objectively evaluate its associated workload. We discuss how this can be used to improve staffing decisions and routing workload dynamically through real-time monitoring of emotional load.

1. Introduction

Research on service delivery reports extensively on the impact of operational factors on worker productivity. Most of this research focuses on the impact of system-level load, as measured by the number of customers per worker, on employee productivity (e.g. Kc and Terwiesch (2009)). However, service delivery involves people—both workers and customers—who inevitably vary in their behavior, the emotions they express, and the ways in which they respond to other people. We posit that studying customer emotion is particularly critical for understanding factors affecting service delivery and can substantially contribute to the understanding and improvement of service systems.

Understanding the role of customer emotions in service interactions is critical because customer emotions impact employee performance (Rafaeli et al. 2012) and service outcomes (Barnes et al. 2010). Yet, emotions are generally ignored in operations research (Field et al. 2018). Research on the interpersonal effects of emotion in Organizational Behavior describes the effects of one's emotions on the people with whom he or she interacts (Hareli and Rafaeli 2008). Partners to a conversation mutually influence each other (van Kleef et al. 2004), an influence that is salient in service interactions. Customers are at liberty to express emotions, while agents must restrain and are emotionally labored (Grandey et al. 2010). Agents must express a specific type of emotion (e.g. "service with a smile" (Pugh 2001)) and suppress negative emotions that customers invoke. Lab experiments show that customer emotions affect the speed, accuracy and fatigue of service agents (Rafaeli et al. 2012). Moreover, negative customer emotions (as pronounced by verbal aggression) also lead to incivility of agents (Walker et al. 2017), thus suggesting a reciprocal cycle of influence between customer emotions and agent behavior.

This research develops a methodology to analyze customer emotions expressed in their communication with service agents and measure its impact on the behavior of service agents, which is important to evaluate productivity and optimize work allocation. To the best of our knowledge, available studies on emotion effects have not examined actual, real-time customer-agent conversations, and thus provide only limited insights for operational implications; research in psychology relies extensively on lab studies in which participants simulate service interactions (cf. Rafaeli et al. 2012), and on self-report measures (cf. Wang et al. 2011). Moreover, there isn't much work studying the impact of positive emotions on service agents. Our work extends the current research into an understanding of the emotional elements of service interactions in two important ways: (i) predict and test the effects on micro-level large-scale data of real service conversations and (ii) consider the effects of a range of customer emotions (from negative to positive) on service agents, using an objective approach to measure these emotions, which can be replicated in other contexts. We assert that service interactions vary in the amount and valence of customer emotions that agents encounter and must handle. Analogous to the operational construct of offered load, which measures the amount of working time required for service delivery, we conceptualize ***emotional load*** as the amount of customer emotion that a service agent encounters and must handle at work. Handling customer emotions is an important aspect of service delivery: many service organizations require their employees to address customer emotion (Grandey et al. 2010) and provide "service with a smile" (Pugh 2001).

The context of this study is contact-center service, which is technology-mediated, and therefore provides opportunities for detailed measures of both agents and customers behavior (Rafaeli et al. 2017). The analyses are conducted at an extremely high resolution of detail, namely the level of individual messages within individual customer-agent conversations, using panel data based on a cross-section of identified agents that provide service to multiple customer requests. We use objective measurements of customer emotion and agent behavior, thus overcoming limitations of previous research (Rafaeli et al. 2017). Specifically, our work relies on advances in text analysis and use automated sentiment analysis engines (Thelwall 2013, Yom-Tov et al. 2018) to provide real-time objective estimation of customer emotion from text messages. We analyze a dataset of 141,777 conversations between customers and service agents of a large western transportation company. The data includes multiple operational measures. Our main dependent variable—agent Response Time (RT)—is the time an agent spends reading, processing, and responding *to a specific message of a focal customer*, and includes the time an agent spends on handling other parallel customers.

This study tests empirically how emotional load impacts employee behavior by influencing (a) agent RT to customers, (b) agent effort (measured as the length of text agent writes), and (c) the number of customer and agent messages required to complete the service. An important challenge arises in estimating the causal effect of customer emotion on agent RT, a key objective of this study. Omitted factors related to problem complexity affect both customer emotions and the amount of work performed by an agent (which translates into RT). For example, if a solution to a problem requires multiple interdependent stages thus generating a longer RT, a customer might express frustration. In addition, there is a simultaneity problem: customer emotion and agent RT affect each other. These problems may produce an endogeneity bias in the estimation. We circumvent these problems by performing our analysis at the individual message level, treating the service chat as panel data and also using Instrumental Variables (IVs) as a source of identification; the instruments are formulated based on exogenous shocks to agent behavior that have been previously documented in the service operations literature. Another concern we address in this paper is measurement error associated with quantifying customer emotion. To solve that we use an IV approach with two sentiment analysis tools (see Section 4). Despite the presence of conflicting theories and predictions (see Section 3) our analyses show that as customer emotion moves from positive to negative emotion, agents put more effort in each response, RT becomes longer, and the number of turns it takes to complete the service increases.

We also consider a reversed effect of agent behavior on customer emotions. Emotions expressed by customers, both negative (e.g., anger, frustration, irritation) and positive (e.g., cheerfulness, happiness), provide cues of customer perceived service quality. Expressions of positive emotions by customers indicate satisfaction with the service, while negative emotions indicate discontent, and likely suggest that service issues are not addressed (Yom-Tov et al. 2018). Therefore, we expect that agent behavior will affect customer emotions. The prediction here depends on whether the customer perceives RT as related to service or wait time. Since agent RT also include delays due to multitasking it is important to understand how RT is interpreted by customers. We examine how the ways agent signals their effort (either by answering quicker, writing longer messages, or more messages) are interpreted by the customers by their effect on customer emotions. This analysis carries implications to the way agent should priorities their work (between angry and happy customers) and communicate their effort to customers, as well as implications to the acceptable level of in-service-wait (i.e. waiting during customer length-of-stay) that results from concurrency decisions.

Our paper demonstrates the importance of measuring and documenting micro-level variations of load *within service conversations*. Previous research in Operations Management documented effects of system load on employee efficiency (Delasay et al. 2019), measuring load by number of people in a queue (Song et al. 2015) or number of customers per agent in a system (e.g. Kc and Terwiesch (2009)). Findings show ambiguous effects of system load, in some cases being shown to increase efficiency and in other cases to decrease efficiency. Delasay et al. (2019) therefore called for research on mechanisms that might drive these effects (e.g., Batt and Terwiesch (2017)). Consistent with recent calls to incorporate behavioral phenomena into Operations Management research (Cho et al. 2019), we suggest that considering aspects of emotional load can enhance our understanding of agent behavior.

Our analyses integrate a Service Operations perspective with Organizational Behavior theory into a multidisciplinary view of service systems to provide the following contributions:

1. We propose a new construct of emotional load, as distinct from the known construct of system workload, building on Organizational Behavior theory. The construct highlights the role of emotions in service operations. We develop and test a systematic and objective methodology to measure emotional load in real-time, and show that these measures are effectively impact agent behavior.

2. We use micro-level data to quantify the causal effect of customer emotions on three performance indicators that can be linked to productivity: RT, extension of messages, and length of service conversations. Agent RT tend to be longer for customers that express negative emotions,

relative to those that express positive emotions. In terms of magnitude, a customer with negative emotions (one standard deviation below the mean) increases the agent RT by 16.7%, an effect that is 3.6 times stronger in magnitude than of agent multitasking and 13 times stronger than system-level load (queue length). The text length written in chats, as a response to negative emotions, is 32% longer than in neutral chats while positive emotion shorten text length by 15% compared to the text of neutral chat.

3. The analysis also reveals a reversed effect of agent RT on customer emotions. We show that to reduce sentiment by 1 SD the RT need to increase by 5 minutes. Long RT is also a result of multitasking and load. In Section 6, we discuss how the organization can use real-time sentiment analysis tools to improve customer sentiment.

4. Our results support the claim that emotional load is an essential characteristic of workload that needs to be taken into account in the design of contact centers and the control of service systems. We show how these empirical results can be used to improve staffing and work allocation decisions in contact centers. And discuss several ways of how an organization can leverage the information regarding customer emotions to improve the contact center operations.

2. Context of the Study and Data Description

This study is based on data provided by LivePerson Inc. (https://www.liveperson.com), a platform for customer service contact centers. LivePerson offers a web-based service platform, which allows end customers to interact with service agents through written messages—a "chat" between a customer and an agent. Service-agents are employees of the service brand, and work through the LivePerson service platform, so LivePerson servers mediate the communication between service-brand agents and customers. Customers who visit a company website may be invited to a chat, and those who agree are transferred automatically to available service agents. Customers can also actively request a chat service. If no agents are available, customers must wait. Service chats comprise iterations of agent and customer written messages. A feature unique to chat service platforms is that unlike in the case of phone service platforms, agents can simultaneously interact with multiple customers. Still, there is a limit to the number of customers that agents can simultaneously interact with; agents are considered available only if they are both online and interacting with less than the maximum number of customers (3 in the case of data used in this study). Once a customer is assigned to an agent, the service (chat) begins. Note that customers are not explicitly informed of this multitasking practice. Employees waiting for a specific customer to react may turn to interact with other customers. When an agent is busy with a particular customer, other concurrent customers may need to wait (we call this waiting during service "in-service-wait"). But the waiting customers do not know the reason for the agent's delayed RT as there are no indicators in the customer interface about any other customers present in the system. When the service is complete, customers exit the system.

2.1. Data Description and Definitions

We obtained data of 162,362 conversations conducted during the period March 2016 to April 2017 between customers and service agents of a western transportation company. The data include three types of entries: employee lines, customer lines and system lines. The latter are messages that are automatically generated, and do not reflect any human behavior, therefore we removed them from the analyses. From here on we use the terms “chat” and “conversation” to refer to a full service interaction between an agent and a customer. The terms “line” refers to some text that a customer/agent sent (i.e., pressed “enter”) and “message” refers to a group lines that a customer/agent sent one after the other, uninterrupted. That is, one a customer/agent sent a few lines in a row, we collapsed them to a single message. Figure 1 presents a schematic diagram of simultaneous chats being handled by a particular agent. Each of the three chats illustrated in Figure 1 is with a different customer, and each chat involves multiple messages sent by an agent and a customer. Within our sample, a chat lasts on average 12.11 minutes with standard deviation of $SD = 9.95$, and has on average 5.28 customer messages ($SD = 3.75$) and 5.68 employee messages ($SD = 3.701$).

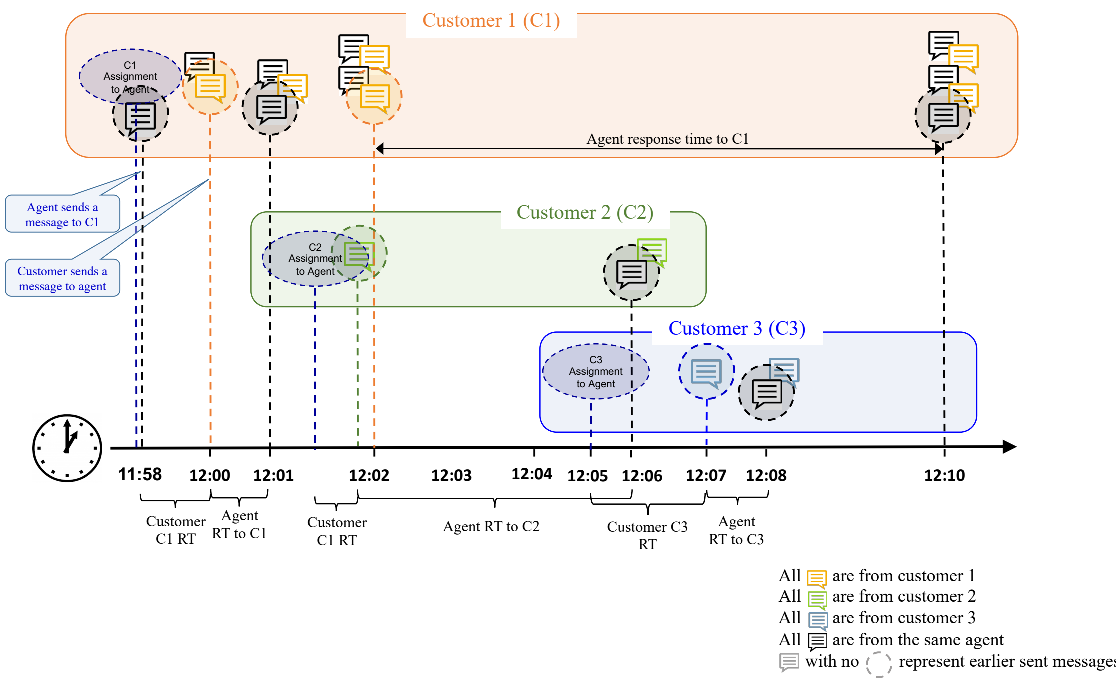
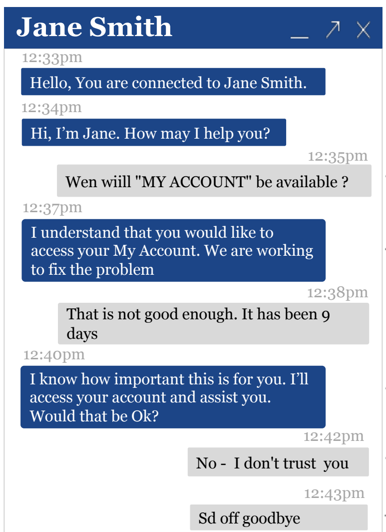


Figure 1 **Example of Agent-Customer Data Flow**

Each chat is identified by chat ID, employee ID, date, type of service (sales or support), and the time the customer waited in the queue before the chat started. Each line in the data, of a specific chat, contains the following information: a time-stamp of when the line was sent, a notation of who wrote that line (customer, agent, or system), number of words in the line, and a score of the customer expression of emotion in the line. Due to privacy considerations we do not have direct access to the text itself or to any demographic indicators of customers and employees. Figure 2 provides an example of such a chat.



Section	Agent Response Time	Sentiment	Turn
Agent	30 sec		1
Customer		0 (neutral)	2
Agent	75 sec		3
Customer		-1 (negative)	4
Agent	82 sec		5
Customer		-1 (negative)	6
Customer		-2 (very negative)	6
Total			6

Figure 2 **Example of Agent-Customer Chat and Measures**

The main goal of this study is to link customer expressed emotion with agent behavior that can be linked to measures of productivity. Usual measures of productivity include the total throughput time of a conversation and total number of customers that can be served by an agent (i.e. throughout rate). We identified two performance indicators of agent behavior that are directly linked to these measures of productivity: 1) RT of the agent to each individual customer message and 2) number of turns in a conversation. Each time a customer sends a message, there is an elapsed time until the agent sends a response. We define this time interval as agent RT to the focal customer message. Theoretically, agent RT can be further decomposed into: (i) time an agent spends doing background work for the focal customer and writing the response message; (ii) time spent working for other customers (including background work and writing messages). Unfortunately, the data does not provide details of the time an agent allocates to different tasks. As a second best, we use the number of words on each agents response message as a proxy for the effort and time the agent dedicated to a focal conversation.

We use agent RT as our main measure of agent behavior for the following reasons: first, changes in agent RT translate directly into agent efficiency. Second, RT is the wait time that customers actually observe, since customers cannot distinguish between the time an agent is working on their needs versus working for other customers. Finally, we note that RT is influenced by the extent of agents' multitasking. Since, we cannot disentangle *precisely* agent RT to the service time of a focal customer and the service time of other (concurrent) customers, we control for agent multitasking by measuring concurrency—the number of customers an agent serves simultaneously.

2.2. Measuring Customer Emotions in a conversation

Research on emotions in psychology and Organizational Behavior groups discrete emotions into two categories: negative sentiment, which includes emotions such as anger, frustration, irritation, annoyance, disappointment, anxiety, or stress, and positive sentiment that includes emotions such as gratitude, enthusiasm, happiness, contentment, sympathy, satisfaction, trust, relief and calmness (Feldman-Barrett and Russell 1999). Service interactions can involve both negative sentiment, and positive sentiment (Herzig et al. 2016). Rather than studying the effects of specific emotions, a common research focus and our focus here as well, is on the presence and impact of positive and negative sentiment as two sides of a single scale (Watson et al. 1988). From here on we use the terms "emotion" and "sentiment" interchangeably to refer to customer expressions of emotion during a service chat.

To measure customer emotions we take advantage of recent progress in Natural Language Processing, specifically automated sentiment analysis. A diverse set of tools are available: tools that are based on word count (i.e. counting words from labeled dictionaries; e.g., *LIWC*, Tausczik and Pennebaker (2010)), those who add additional NLP layer of grammatical aspects (*SentiStrength*, Thelwall (2013); CustSent, Yom-Tov et al. (2018)), and tools that are based on Neural Networks (*Stanford*, Socher et al. (2013)). In the current study, we use two sentiment analysis tools, *SentiStrength* and *CustSent*. The *SentiStrength* tool was designed to estimate the strength of positive and negative sentiment in short texts. It estimates sentiment in both formal and informal language and has human-level accuracy for short social web texts. The *CustSent* tool was designed for assessing sentiment in a conversational context. Both tools utilize labeled dictionaries, as well as NLP techniques, and their accuracy was validated to customer service context by LivePerson. Both were found to be superior to other tools in this context, and although *CustSent* has higher precision, *SentiStrength* has higher recall values (Yom-Tov et al. 2018). (See Appendix EC.1 for data regarding recall and precision of both tools.) As we show later, our analysis combines these two alternatives to measure emotions to reduce measurement error in our empirical study (see Section 4).

SentiStrength provides a number that represents the assessed valence and intensity of detected emotion. Negative scores represent negative emotions and positive scores represent positive emotions. The value of the score indicates the intensity of the emotion. The range of the SentiStrength sentiment score is limited between -5 and +5. For example, the following sentence is coded as (+1):

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

In contrast, the following sentence is coded as (-1):

"This is way too expensive for a local call."

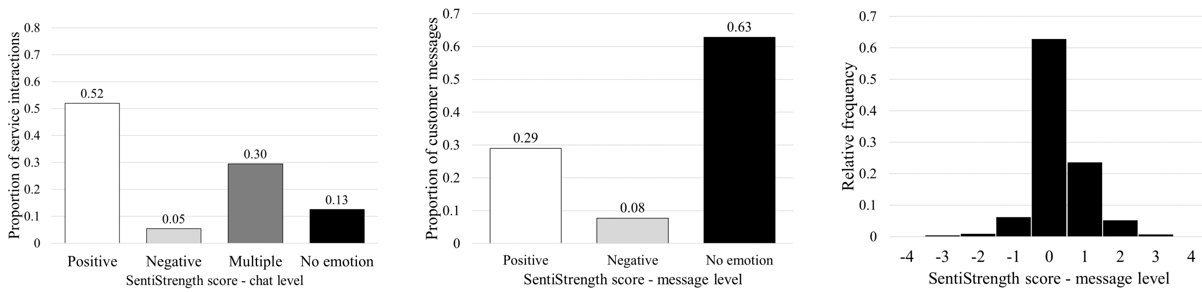
We use the score of negative (positive) customer sentiment as a proxy of high (low) agent emotional load; they represent the emotional elements that agents must handle in the process of their work, in addition to performing the required service tasks. Figures 3 provides some descriptive statistics that illustrate the variation of customer emotions as evaluated by SentiStrength across customer conversations with agents. Figure 3(a) shows the proportion of chats that include only positive/negative emotion, multiple emotion (both positive and negative) or no emotion; given that more than 85% of chats include emotion, this positions emotion as a central feature of service interactions. Figure 3(b) shows the proportion of customer messages that express positive/negative or no emotion; this demonstrates that on a message level most of the conversations are mostly technical (without emotion) and, contrary to general assumptions, positive emotions are more frequent in service conversations than negative emotions. This is also demonstrated in Figure 3(c), that shows the distribution of emotion intensity at the chat level.

Figure 4 provides a preliminary description of the association between customer emotion and agent RT. The plot shows a kernel smoothing of average agent RT (along the whole chat) as a function of average customer emotion (in that chat), suggesting a strong relationship between emotional load and agent RT. As previously mentioned, this correlation does not necessarily imply a causal effect, as it is important to control for multiple factors that can affect these two outcomes. The next section formulates the main hypothesis that relates employee productivity with customer emotion, to be tested with the econometric framework presented in Section 4.

As in SentiStrength, CustSent also provides a number that represents the assessed valence and intensity of detected emotion. The value of the score indicates the intensity of the emotion (the strength of the negative or positive emotion). Though there is no hard limit on the range of the sentiment score, in practice, the scores for emotion in our dataset range between -12 and +10. The above two exampled sentences are coded as (+2) and (-2), respectively, by this engine.

3. Theory Development

In this study we measure emotional load of agents using a sentiment analysis tool which measures positive/negative customer emotions in an online chat-type contact center, and link it to agent



(a) Full Service Chat (b) Customer Messages (c) Sentiment Distribution

Figure 3 Frequency of Emotion in Customer Service

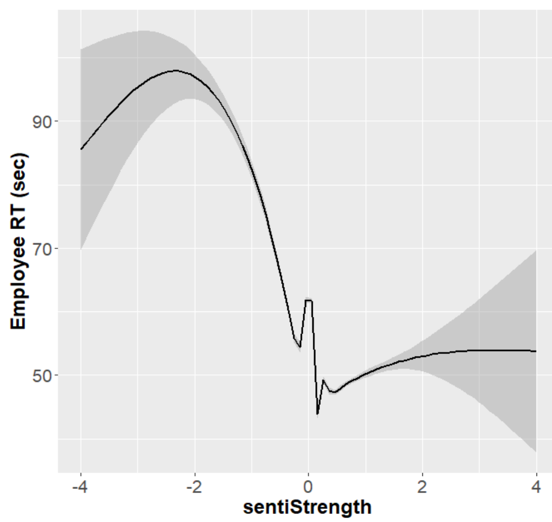


Figure 4 Agent Productivity—Measured by the Average Agent RT to Customer Messages—as a Function of Customer Sentiment. The Gray Area Around the Curves Represents 95% Confidence Interval.

behavior: response time, the length of messages and the number of messages required to complete a service request. Our analyses aims to disentangle the mutual influence of the inputs of both partners of a service interaction.

Expressions of negative customer emotion create additional work that service agents cannot ignore (as reviewed in §1). Thus one can view such emotions as a type of load. In this paper, we use customer expressed emotion as a proxy to agents' emotional load. We assume that customer expressions of negative emotions create high emotional load on the agents whereas customer expressions of positive emotion create low emotional load. In this section, we combine Organizational Behavior theory with Operation Research theory to predict how customer expressed emotion should influences the behavior of service agents (§3.1) and how agent behavior should influences customer emotion (§3.2).

3.1. Effects of Customer Emotions on Agent Behavior

3.1.1. Response Time (RT) Lab experiments show that exposure to negative customer emotions reduces agents cognitive capabilities by hampering working memory, recall of customer requests and quality of performance (Rafaeli et al. 2012). In a similar vein, encounters with anger are likely to evoke a sense of fear, and fear produces an urge to escape or avoid that situation (Marsh et al. 2005). In a contact center with concurrency an agent can "escape" by delaying responses to a customer expressing anger and prioritizing other (concurrent) customers; this would translate into a longer overall RT to the angry customer. Based on these findings, we predict that agents who encounter customers expressing ***negative*** emotions will have an ***increased RT***.

Congruently, ***positive*** customer emotion might ***reduce agent RT***. Interacting with people who display positive emotions makes people happy about their situation (van Kleef et al. 2004). As Walker et al. (2017) showed, positive customer emotions help replenish employee resources, and improve employee self regulation. Therefore, we expect agents who encounter positive customers to have higher motivation and more cognitive resources (Bakker and Demerouti 2007), both of which will increase agents' efficiency. In addition, since positive customer emotions create a more pleasant work experience for agents, we expect that agents who encounter a customer expressing positive emotion will return faster to that customer. All this suggests a shorter RT to customers expressing positive emotions.

Additionally, Emotional Contagion theory (Hatfield et al. 1993) suggests that positive/negative customer emotion will spillover to the agents that interact with them: negative customer emotion will evoke negative agent emotions, which may reduce agent focus and efficiency, while positive customer emotions will evoke positive agent emotions and increase agent motivation, broadening their attention span (Vacharkulksemsuk and Fredrickson 2013). Through this lens, ***negative customer emotions*** would reduce efficiency and therefore increase RT, while ***positive customer emotions*** would improve efficiency and therefore reduce RT. Since agents regulate their expressed emotions according to company policy (Rafaeli and Sutton 1987), we are not able to test this theory directly. The general prediction of this theory, however, aligns with the our predictions above. Thus, our first hypothesis is:

HYPOTHESIS 1. *A deterioration in customer emotion (moving from positive to negative) increases agent RT in the subsequent agent message*

An alternative prediction is that agents might speed-up their work in response to customer expressions of negative emotion since they are motivated to end interactions with these customers (Marsh et al. 2005). Negative customer emotion may put agents in what regulatory focus theory (Higgins 1998) labels "prevention focus," which may manifest in agents trying to end interactions with customers who express negative emotions quickly. Also, negative emotions can urge agents to work harder. Negative customer emotion can be viewed as a signal of customer dissatisfaction (van Kleef et al. 2004) and since service agents are assessed by satisfaction of customers, they might try to repair the damage as quickly as possible. Hence a contradictory hypothesis to hypothesis 1 is:

Hypothesis 2. *A deterioration in customer emotion (moving from positive to negative) reduces agent RT in the subsequent agent message*

3.1.2. Effort Reflected in Length of Messages Customer emotion might affect the effort that an agent puts into service. Noticing and comprehending customer emotions is a distinct task and must be performed in addition to attending to customer requests (Vilnai-Yavetz and Rafaeli 2003). An agent that encounters customer emotions must realize and display organizationally appropriate responses to these emotions (Geddes and Callister 2007)—in itself a demanding task of "Emotional Labor" (Rafaeli and Sutton 1987, Grandey et al. 2010)—therefore, when agents encounter an emotional customer message, additional effort is required on their behalf. This extra effort should be evident in the length of the response they write to the customers. As negative customer emotion signals dissatisfaction, agents are expected to put more effort into responses; for example in addition to solving the service request, agents may acknowledge the frustration that a customer is experiencing, or apologize for the delay, thus leading to a longer textual response. Therefore:

Hypothesis 3. *A deterioration in customer emotion (moving from positive to negative) increases the number of words an agent writes in the subsequent message*

In contrast, as we argued before, negative customer emotion is demotivating while positive customer emotion is motivating; such motivation may increase the amount of information that an agent communicates to the customer. Positive customer emotion might be also energizing for agents (Bakker and Demerouti 2007). If agents are strengthened by positive customer emotion, they may be more likely to invest more effort. Therefore, we consider a competing hypothesis:

Hypothesis 4. *An improvement in customer emotion (moving from negative to positive) increases the number of words an agent writes in the subsequent message*

3.1.3. Number of Turns Rafaeli et al. (2012) showed in lab experiments that exposure to negative emotions reduces agent's cognitive capabilities and increases agent errors. If an agent is less focused it may take him or her more inquiries (messages) to understand customer problems. Moreover, if more errors are being made by the agent then we expect more turns (rounds of messages) will be required to complete the service. Therefore, we pose the following:

Hypothesis 5. *A deterioration in customer emotion (moving from positive to negative) increases the total number of turns in a conversation.*

A competing hypothesis is equally plausible. As we argued before, agents might be motivated to end interactions with customers who express negative emotions (Marsh et al. 2005). Since these expressions are signals of an aversive situation, agents are likely to be as concrete as they can with the customers and aim to end the interaction with fewer exchanges as possible. Interviews with service agents, as reported by Sutton and Rafaeli (1988), suggest that displays of positive emotions in face-to-face service interactions create more customer engagement. If a spillover effect exists then the number of turns in a chat should increase in service encounters involving positive customer emotions. In addition, since positive emotions create a more pleasant work environment, agents may be motivated to spend more time with the positive customers and thus exchange with them more messages. Accordingly we can also pose:

Hypothesis 6. *A deterioration in customer emotion (moving from positive to negative) reduces the total number of turns in a conversation.*

3.2. Effects of Agent Behavior on Customer Emotion

3.2.1. Response Time (RT) Theory and previous empirical evidence suggest that agent behavior can itself impact customer emotion. Customers expect the attention and dedicated focus of their service agent. They strongly dislike waiting (Maister 1984, Larson 1987, Taylor 1994) and might even abandon the service in response (Mandelbaum and Zeltyn 2013, Allon et al. 2011). Due to the remote nature of the service interaction (as opposed to face-to-face interactions), chat service leaves customers totally detached from the service agent, with no ability to see any progress toward the service goal. This creates an unexplained wait which is perceived as longer than the actual wait for the agent response the customer experiences (Larson 1987), and therefore may create frustration. Moreover, as explained, in chat-based services, agent RT includes also in-service-wait (that is created by concurrency). The effect of waiting on customer emotion is expected to be even more profound when agents are serving multiple customers in parallel (Goes et al. 2018). Thus, we believe that long RTs might negatively affect customer emotion. If agent RT is perceived by the customer as unnecessary waiting, we expect that:

Hypothesis 7. *An increase in agent RT deteriorates customer emotion (moving from positive to negative) in the subsequent customer message*

In contrast, there is evidence that longer services are of better quality, and are perceived as such by the customers (Anand et al. 2011). Due to the remote nature of the service interaction, customers may not be aware of the fact that they are also waiting for the agent to serve other customers (in-service-waiting) and therefore may perceive all the RT as service time. Furthermore, Buell and Norton (2011) showed that if customers perceive the waiting as being a result of agent effort (a.k.a. the "illusion" of labor) their perceived value and satisfaction increases. Therefore, they suggested the use of transparency tools for projecting agent effort and increasing customer satisfaction. In contact centers, agent labor is communicated via indicators of agent responsiveness (short RT), the length of text and the number of messages the agent writes. We expect that as these three indicators improve customer satisfaction and expressed sentiment will increase too. So, if RT is perceived by the customer as labor, we expect that:

Hypothesis 8. *An increase in agent RT improves customer emotion (moving from negative to positive) in the subsequent customer message*

3.2.2. Effort Reflected in Length of Messages If the number of words agents write is a proxy of their effort, customers who encounter long agent messages may believe that the agent puts extra effort into solving their issues. This "extra" attention might lead customers to feel as if they are being taken care of, thus leading to greater satisfaction. In the same spirit, shorter messages might signal less effort on the agents behalf and the service might be seen as superficial, thus leading to customer anger or frustration. Hence, we hypothesize that:

Hypothesis 9. *An increase in the number of words the agent writes improves customer emotion (moving from negative to positive) in the subsequent customer message*

3.2.3. Number of Turns Lastly, if a service episode takes too many turns to complete, customers may perceive the service as unprofessional, even though the agent is putting in more effort (Anand et al. 2011). This could signal to the customer the existence of a problem that the agent is unable to solve and lead to customer dissatisfaction—this may then translate into more expressions of negative emotion as the conversation extends. Thus, our final hypothesis is:

Hypothesis 10. *As a conversation increases in the number of turns, customer emotion deteriorates (from positive to negative)*

In the remainder of this paper, we empirically untangle the complex relationships between customer expressed emotion and agent productivity.

4. Econometric Specification

In this section we develop an econometric framework to test the causal effect of customer emotion on agent productivity. An important challenge in the estimation arises due to omitted factors related to the complexity of the focal case handled by an agent. Cases of higher complexity are likely to be associated with longer agent response time, because they require more effort to handle them; more complex cases are also likely to be related to customer emotion. Although we can include some observable proxies of case complexity in the model, there are other dimensions of complexity which cannot be measured and therefore become confounders that can bias the estimates. A second complication is reversed causality between agent productivity and customer emotion, whereby longer response times may enhance customer frustration. This produces a simultaneity problem between customer emotion and agent productivity: cases that take longer to handle also tend to have negative customer emotions, but it is not clear what is the causal relationships between the two.

The empirical strategy used to identify the causal effect of emotion on agent productivity is to exploit the panel structure of the data, using the variation across the sequence of messages within a conversation as a source of identification. Let i index the customer-agent conversation associated to a case and let $NTurns_i$ denote the number of turns, with $t = 1 \ldots NTurns_i$ representing each turn within that conversation. The variable EMO_{it} measures the emotion of customer message in turn t, and RT_{it} the agent response time in a message t. Response time (RT) is modeled as:

$$\log(RT_{it}) = \delta_i + \beta EMO_{it-1} + \gamma W_{it} + f_t(\theta) + u_{it}, \tag{1}$$

where δ_i is a fixed effect for the conversation, W_{it} are workload related factors that vary during the conversation, u_{it} is an error term and $f_t(\theta)$ is a parametric function capturing changes through the progression of the conversation. The latter is included because other applications with similar data revealed that EMO has a positive trend during a conversation (Yom-Tov et al. 2018); a trend that is crucial to control for. To account for this, the covariate $f_t(\theta)$ is specified to capture the stage of the conversation i where the focal turn t occurs, defined as $ConvStage_{it} = t/NTurns_i$. This control variable is included in all the econometric models analyzed at the conversation-message (it) level.

The fixed effect δ_i controls for several unobserved factors that could lead to omitted variable bias. In particular, it captures the complexity of the case, which by definition does not vary during the conversation pertaining the same case. Because conversations are relative short (12.11 minutes, SD=9.95), effects due to day of the week and hour of the day are also captured by δ_i. Because a conversation is handled by a single agent, all agent related factors are also absorbed by the fixed effect.

Previous work showed several mechanisms that relate workload and its composition to agent productivity (for a review see Delasay et al. (2019)). Workload can affect the speed of an agent's work through fatigue, thereby reducing productivity and compliance with process standards (Dai et al. 2015). On the other hand, current and pending workload can put pressure on an agent to work harder and increase productivity (Tan and Netessine 2014, Kc and Terwiesch 2009). In settings with a shared queue among multiple agents, social loafing can lead agents to slow down when facing a long queue (Wang and Zhou 2016). To capture the effects of the customer queue, a covariate measuring the number of customers in queue at the beginning of the response time interval, $NumInQueue_{it}$ is included as a control.

In chat contact centers, it is common for agents to handle multiple conversations simultaneously. This type of workload can also create fatigue and pressure effects. Moreover, handling simultaneous conversations is a form of multitasking, which is also a determinant of labor productivity in services (Kc 2013, Goes et al. 2018, Bray et al. 2016). The number of concurrent chats ($Concurrent_{it}$) is measured by taking an average over the time interval covered by the response time. Given the dynamics of work assignment in a customer contact center, both $NumInQueue$ and $Concurrent$ can vary substantially during the course of a conversation; these two variables are the main covariates included in W_{it}. Other workload related effects, such as the hours elapsed during the working shift, do not vary much during a conversation due to its short duration, and are therefore absorbed in the fixed effect δ_i.

Identification in this model is driven by the variation in emotion across customer messages during the same conversation. Recall that one of the concerns regarding the identification of the causal effect of emotion on agent behavior was reverse causality: it is possible that EMO and RT affect each other. However, the regression model (1) exploits the sequencing of the messages to avoid this reverse causality. The variable RT_{it} is measured *after* the customer expresses emotion in his/her message on turn $t-1$, hence it could not have influenced EMO_{it-1}. Furthermore, the detailed controls in the model—including the conversation fixed-effect δ_i—controls for most of omitted variables related to case and agent heterogeneity, providing a clean identification strategy.

A final concern for identification is measurement error on the EMO variable, which could lead to an attenuation bias in the coefficient associated to it. Recall that the main measure of EMO used in the analysis is *SentiStrength* (Thelwall 2013). To mitigate concerns about measurement error, an alternative measure of customer emotion was constructed using the methodology developed by Yom-Tov et al. (2018). The main differences in the computation of the two measures are in the dictionaries they use and in their range of sentiment scores ($SentiStrength$ scores range between -5 and +5, whereas $CustSent$ has no hard limit on the range of the scores.) Nevertheless, the two measures are highly positively correlated ($r = 0.630, n = 1,065,079, p < 0.001$), and hence the alternative emotion measure is a useful Instrumental Variable to eliminate measurement error (Wansbeek and Meijer 2000).

4.1. Decomposing the Effect of Customer Emotion on Agent Behavior

The effect of customer emotion on agent response time can be decomposed into two parts: (1) it can affect the effort that the agent exerts to respond to each customer message, thereby increasing the time required to write a response; (2) it can change the behavior of the agent in terms of the priority it puts on the focal conversation, relative to other concurrent conversations. The data do not contain specific information about the time the agent is spending on writing and back-office work for each individual case, so these two effects cannot be perfectly separated out. As a second best, the number of words in the agent's response message is a reasonable proxy for the amount of work the agent spends answering to a message. To disentangle these effects, the number of words in the agent message ($NumWords_{it}$) is included in the specifications as follows:

$$\log(RT_{it}) = \delta_i + \beta_1 EMO_{it-1} + \beta_2 log(NumWords_{it}) + \gamma W_{it} + f_t(\theta) + u_{it}; \tag{2}$$

$$log(NumWords_{it}) = \delta_i + \beta_3 EMO_{it-1} + \gamma W_{it} + f_t(\theta) + v_{it}. \tag{3}$$

This specification, which includes the same control variables as in model (1), captures two paths through which EMO can affect agent productivity. Coefficient β_3 captures the effect of customer emotion on the effort the agent makes to respond to the message, using $NumWords$ as a proxy for effort. As discussed in section 3, this effect is ambiguous: it is possible that the negative emotion induces more or less dedication of the agent's effort to the focal case. This effect translates into an impact on RT because longer text needs more time to write ($\beta_2 > 0$). In addition, the coefficient β_1 captures other effects of emotion on RT, in addition to the effect that operates through $NumWords$. To the extent that the number of words is a good proxy for agent effort spent responding to the customer, β_1 can be interpreted as the impact of emotion on agent behavior in terms of the effort given to the focal conversation. It is possible though that the number of words is not a perfect proxy, and that β_1 may also include other effort-related activities not reflected in the extension of the agent's written message (e.g., scrutinized search in the Customer Relationship Management software). We do not have documentation of agents activity outside of the chat platform, and therefore cannot measure the full agent effort directly. Despite these limitations, models (2) and (3) provide information about the alternative paths through which customer emotion affects agent productivity which could be relevant for managerial purposes.

Equations (1) and (2) capture the effect of customer emotions on the response time to each individual customer message. However, it is also possible that customer emotion affects the number of turns ($NTurns_i$) required to address a case, which is also directly related to agent productivity. Estimating the effect of emotions on the number of turns of a conversation requires a different identification strategy. In the previous models, identification is driven by the variation across turns within a chat. This identification strategy cannot be applied to model the number of turns, which is a variable that we measure at the conversation level. In other words, a conversation is the basic unit of analysis we used to study the number of turns $NTurns_i$. The model includes the effect of emotion in the first customer message of the conversation, EMO_{i1}. One may be tempted to average all messages across the conversation, but this is problematic due to the reverse causality problem discussed earlier: emotion affects agent productivity but also vice-versa. In addition, the data reveals that customer emotion tends to improve (become positive) towards the end of the conversation, so a significant portion of the cross-sectional variation in emotion across conversations is driven by the initial messages. Because the number of turns can also be affected by the workload of the agent, the average concurrency during the whole conversation, $Concurrent$, is computed as before, and $NumInQueue$ here is calculated by the number of customers in queue when the conversation started (these variables are exogenous, so it is possible to average $Concurrent$ across all turns). The following regression model is used to estimate the impact of emotion on the number of turns:

$$NTurns_i = \rho_{a(i)} + \beta_4 EMO_{i1} + \gamma W_i + \psi X_i + w_i. \tag{4}$$

The term $\rho_{a(i)}$ is a fixed effect of the agent serving chat i and w_i is an error term. The other covariates in the model are discussed next.

Model (4) is estimated using a cross-section of conversations, therefore it is important to control for case complexity. The number of words in the first customer message ($CustWords_1$) is an exogenous variable used to proxy the complexity of the case, included as a covariate with log transformation (to keep consistency with the previous models). To capture seasonal effects, a weekday-weekend dummy and hour of the day dummies are included ($IsWeekend$ and $HourOfDay$, respectively). The type of service case ($SrvType$) is controlled through a dummy variable. Finally, changes in the agent productivity due to fatigue are controlled with dummy variables for each hour worked during the shift ($ShiftTime$). These are the covariates included in the set of controls denoted by X_i.

Interventions and prescriptions to improve agent productivity depend on whether the impact of emotion on agent productivity is generated through the response time, the number of words written by the agent or the number of turns in the conversation. The econometric models described above are useful to disentangle these effects, which are discussed in Section 6 in terms of their managerial implications.

4.2. Modeling the Effect of Agent Behavior on Customer Emotion

It is also of interest to study how customer emotion is potentially affected by agent productivity. As discussed in section 3, there are two mechanisms through which response time can affect emotion. Longer RT may be associated to the quality of response provided by the agent, which could have a positive effect on service quality and thereby affect emotion. Alternatively, longer response time could be reflecting lack of attention of the agent for the focal case, thereby reducing service quality and customer sentiment. The variation in response time is influenced by both effects, which makes it difficult to disentangle them empirically.

The empirical strategy we used seeks to uncover these two mechanisms as follows. First, consider the following specification to estimate the effect of RT on customer emotion:

$$EMO_{it} = \delta_i + \alpha \log(RT_{it-1}) + f_t(\theta) + e_{it}. \tag{5}$$

The unobservable e_{it} includes the quality of the response of the agent as perceived by the customer, which is difficult to control with the variables observed in the data. It is then plausible that the response time, RT, will be positively correlated with the quality of the response, as the agent needs to do time consuming work to properly address a customer issue. This positive correlation between RT and the error term induces a positive bias in the estimation of α. Our approach to correct for this bias is to use Instrumental Variables that affect agent RT but do not *directly* affect the customer's emotion. Recall from model (1) that response time is affected by the workload of the agent, W_{it}. In the context of this application, customers do not directly observe the workload of the agent, thereby the effect of this workload can only affect emotion through the response time perceived by the customer. Measuring the effect of RT induced by the variation in an agent's workload is also useful from a managerial perspective, as it provides insights on how workload management and staffing decisions can affect customer emotion.

Model (5) can be further refined by including additional factors associated with agent productivity, specifically, $NumWords$ and $Turn$:

$$EMO_{it} = \delta_i + \alpha_1 \log(RT_{it-1}) + \alpha_2 log(NumWords_{it-1}) + \alpha_3 Turn_{it} + f_t(\theta) + e_{it}. \tag{6}$$

The number of words ($NumWords$) in the agent's message is a proxy for the agent's effort, which is also directly observable by the customer. It is plausible that longer agent messages are include more information to customers or perhaps are perceived by the customer as agent's effort to the focal case, thereby generate positive emotion. On the other hand, the customer has less visibility on the other activities performed by the agent during the response time, and may interpret long RT as lack of dedication, thereby generating negative sentiment. In addition, customer emotion can also be affected by the extension of the conversation, which is captured through the variable $Turn_{it}$, which is the ordinal counts of the current turn in the conversation. Notice that $Turn_{it}$ and $f_t(\theta)$ are positively (but not perfectly) correlated, but the large sample size enables us to estimate their effect separately with reasonable precision. Another potential issue is that RT, $NumWords$ and $Turn$ can be correlated with the complexity of the case—more complex cases require higher effort of the agent and a longer conversation—but recall that the fixed-effect δ_i controls for case complexity, therefore mitigating this omitted variable bias. As before, RT is instrumented with the workload-related exogenous variables W ($Concurrent$ and $NumInQueue$) in order to mitigate the endogeneity bias that can be generated by unobservable quality of the agent's response.

Table 1 summarizes the variables used in all the econometric models described in this section. Panel data models with Instrumental Variables were estimated using Two-Stage Least Squares (2SLS), with the panel data methods developed in Balestra and Varadharajan-Krishnakumar (1987) and implemented in Stata 13 (command xtivreg). The cross-sectional Model (4) was estimated with 2SLS (Stata command ivreg). The next section discusses further specification details, summary statistics and the estimation results.

Table 1 Labels and Coding of all Variables

Variable	Description and coding
Dependent variables	
$NTurns_i$	The number of iterations between a customer and an agent in a conversation i (an iteration is counted when one party answers the second party)
RT_{it}	Agent response time to a focal customer in turn t of conversation i [seconds]
$NumWords_{it}$	The number of words an agent wrote to a focal customer in turn t of conversation i
EMO_{it}	Customer sentiment as measured by SentiStrength engine in turn t of conversation i
W variables:	Agent workload
$NumInQueue_{it}$	Number of customers waiting in queue at the beginning of turn t of conversation i
$Concurrent_{it}$	Weighted average of number of parallel chats handled by the agent during turn t of conversation i
X variables:	Complexity of the problem and time variables
$SrvType_i$	Type of service in conversation i: support (coded 0; 50.81%) or sales (coded 1)
$CustWords_{i1}$	The number of words a customer wrote in the first turn of conversation i
$ShiftTime_i$	The time passed since the shift of an agent started until the beginning of conversation i [hours]
$HourOfDay_i$	Hour of day (8:00-23:00) of conversation i
$IsWeekend_i$	Weekday: Mon-Fri (coded 0; 72.24%) , Weekend: Sat-Sun (coded 1)
Other variables:	
$Turn_{it}$	The ordinal number of the current turn t in a conversation i
$ConvStage_{it}$	The progression of customer or employee turn in a conversation; (computed as the current turn t divided by the total number of turns (NTurns) in a conversation i)
$CustSent_{it}$	An alternative measure for customer sentiment, via CustSent engine, in turn t of conversation i

5. Estimation Results

Table 2 reports the summary statistics of the variables used in the estimation. The top panel shows the variables included in models (1)–(3), with messages as the unit of analysis, the bottom panel shows variables of model (4), with conversation as the unit of analysis. In both cases the sample was previously filtered by dropping outliers, in order to avoid influential points in the estimation. Outliers for the message-level data were selected with the following procedure. We removed observations with RT in the bottom 5% (below 7 seconds); those messages indicate unrealistic RT that were written at the same time that the customer wrote his response, and therefore are more likely to be a response to an earlier correspondence. Observations with RT above the 95 percentile were also removed (the 95% is 1641 seconds). We also removed conversations with data errors in the

Table 2 Statistics of Study Variables

Variable	Mean	Median	St. Dev.	Min	Max
Turn level (N=651168)					
EMO (SentiStrength)	0.27	0.00	0.74	-4.00	4.00
$CustSent$	0.22	0.00	0.72	-12.00	10.00
RT	65.25	47.00	66.10	8.00	1641.00
$log(RT)$	3.84	3.85	0.80	2.08	7.40
$NumWords$	34.58	27.00	26.17	1.00	387.00
$log(NumWords)$	3.30	3.30	0.72	0.00	5.96
$Concurrent$	2.33	2.47	0.73	0.00	3.00
$NumInQueue$	2.52	1.00	3.87	0.00	73.00
$ConvStage$	0.58	0.58	0.27	0.02	1.00
$ShiftTime$	3.63	3.41	2.31	0.00	8.16
$Turn$	8.78	6.00	7.99	2.00	132.00
Chat level (N=141777)					
$NTurns$	10.19	8.00	7.03	2.00	114.00
$log(NTurns)$	2.14	2.08	0.60	0.69	4.74
EMO_1	0.10	0.00	0.62	-4.00	4.00
$CustSent_1$	-0.04	0.00	0.51	-10.00	7.50
RT	64.12	54.50	38.16	7.40	218.86
$log(RT)$	4.00	4.00	0.58	2.00	5.39
$NumWords$	35.06	33.75	12.30	1.00	70.83
$log(NumWords)$	3.49	3.52	0.39	0.00	4.26
$Concurrent$	2.44	2.65	0.58	0.29	3.00
$NumInQueue$	3.13	2.00	4.00	0.00	72.00
$CustWords_1$	26.82	23.00	19.49	1.00	1131.00
$log(CustWords_1)$	3.00	3.14	0.88	0.00	7.03
$ShiftTime$	3.47	3.26	2.27	0.00	7.76

$ShiftTime$ and dropped conversations that were attended after the eighth hour in the agent's shift, to focus on regular shifts (which also corresponds to the top 95%. Lastly, we removed observations with a value of $NumWords$ above the 95% percentile (387 words). Similar procedure was used to select outliers in the conversation-level data reported in the bottom panel (the Max column indicates the cutoffs used to exclude observations). In total, we removed 20,585 chats from the analysis, leaving an effective sample size of 141,777 chats. To check robustness of the results, all the analysis was replicated including outliers in the sample (reported in 5.3).

5.1. Effect of Customer Emotion on Agent Behavior

Table 3 shows the estimation results of econometric models (1), (2), (3), and (4) (each model corresponds to a different column in the respective order). Recall that models (1)–(3) have each message as a unit of analysis, and include fixed effects for the conversation, so the coefficients are estimated using variation across turns of each conversation. In model (4) the unit of analysis is a conversation, including agent fixed-effects.

The key covariate for Model (1) is EMO, the SentiStrength measure of customer emotion. The results reveal a negative and statistically significant effect on RT. Recall that this variable is instrumented using an alternative emotion measure (a different sentiment tool), to mitigate attenuation bias due to measurement error. In terms of the magnitude of the effect, a one point increase in the sentiment of the customer (i.e., emotion becomes more positive) reduces RT by about 20.6% (a 14 seconds reduction for the average RT per message), which is substantial. For robustness, we also ran the model without instrumenting EMO (reported in the online appendix): the coefficient is also negative but smaller in magnitude, consistent with the attenuation bias associated to measurement error.

In terms of the other control variables, *Concurrent* has a positive effect on response time, suggesting that multitasking with multiple customers simultaneously increases the response time to each of them. *NumInQueue* shows a small positive coefficient, suggesting that a longer queue of customers waiting to be attended makes the agent work slightly slower. One possible reason for this results is loafing induced by free-riding (Latané et al. 1979, Wang and Zhou 2016): as agents face more work to be assigned, they work slower so that the work is assigned to other agents. The effect of *ConvStage* is positive and statistically significant, consistent with an increase in RT towards the end of the conversation.

Model (2) includes EMO and the logarithm of $NumWords$ as the main variables of interest. EMO has a negative and significant effect on RT, similar in magnitude relative to the estimates of model (1): a one point increase in EMO reduces response time by 21%. The number of words in the message $NumWords$ has a large *positive* effect on RT, which is expected because a longer text in general takes more time to write. Doubling the length of an agent's message increases RT by approximately 45%. The effect of the other covariates are similar to those reported for model (1), with the exception of *ConvStage* which now has a smaller magnitude: towards the end of the conversation, response time is 4% longer relative to the first message RT. The longer RTs towards the end of the conversation appear to be partially explained by the length of the messages, which is further corroborated by the estimates of Model (3) discussed next.

Model (3) has $\log(NumWords)$ as the dependent variable and EMO as the main covariate of interest, which has a small *positive* effect; the magnitude of the effect is close to zero and negligible. However, additional specifications reported later in this section show that this result is not robust, mainly because the effect appears to be non-linear. Considering the other covariates in Model (3), the effect of concurrent conversations has a negative effect: as agents increase multitasking, they write shorter messages to each customer. The positive coefficient of *ConvStage* indicates that agent messages tend to be longer towards the end of the conversation, which in part explains the longer RT observed as the conversation moves towards completion.

The results of Model (4) are reported in the fourth column. Recall that the unit of analysis in this model is a conversation, and customer emotion is measured in the first customer message (the instrument used for this variable if the alternative sentiment measure *CustSent* in the first customer message). The coefficient of EMO is negative and statistically significant, where a one point reduction in EMO increases the number of turns in the conversation by 1.7, equivalent to

17% of the mean, which is large. This result is aligned with those obtained in models (1)–(3), providing further support that conversations with negative customer emotion tend to be longer and require more time from the agent. In terms of the other covariates, higher number of concurrent customers handled by the agent during the conversation reduces the number of turns required to finish the case, suggesting that agents may be speeding-up to close cases faster when their workload is high.

Table 3 Effect of Customer Emotion on Agent Behavior (Outliers Excluded)

	Model (1) $log(RT)$	Model (2) $log(RT)$	Model (3) $log(NumWords)$	Model (4) $NTurns$
EMO	-0.206*** (0.0028)	-0.209*** (0.0026)	0.007** (0.0025)	
EMO_1				-1.686*** (0.0690)
$Concurrent$	0.057*** (0.0026)	0.075*** (0.0024)	-0.040*** (0.0024)	-1.242*** (0.0369)
$NumInQueue$	0.003*** (0.0007)	0.002*** (0.0006)	0.002* (0.0006)	0.032*** (0.0047)
$ConvStage$	0.246*** (0.0043)	0.040*** (0.0040)	0.463*** (0.0038)	
$log(NumWords)$		0.446*** (0.0015)		
$log(CustWords_1)$				-0.326*** (0.0211)
$IsWeekend$				-0.013 (0.0416)
$SrvType$				6.199* (3.1524)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.616*** (0.0070)	2.228*** (0.0079)	3.113*** (0.0063)	11.134*** (1.6776)
Observations	651168	651168	651168	141777
R^2 Within	.	0.162	0.040	.
R^2 Between	0.018	0.226	0.058	0.011
R^2 Overall	0.009	0.176	0.044	0.003

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 replicates the specifications reported in Table 3 but includes the customer emotion measure in three levels: Negative ($EMO < 0$), Neutral (EMO equals to zero) and Positive ($EMO > 0$).

The Neutral level is the excluded dummy. For models (1) and (2), with $\log(RT)$ as dependent variable, the effect of customer emotion is negative, monotone, and economically significant. Messages with negative emotion receive RTs which are about 35–40% longer relative to messages with positive emotion. These results are consistent with the linear specification presented in Table 3. However, the estimation of Model (3) suggests a different interpretation. Customer messages with negative emotion have responses which are 12.7% longer in the number of words relative to neutral messages. In contrast, customer messages with positive emotion have similar $NumWords$ compared to those with neutral emotion: the coefficient implies a small 2% increase. Hence, the results can be interpreted as a non-linear effect of customer emotion on the extension of the agent's response messages (as measured by $NumWords$), which is decreasing from negative to neutral emotion, and then becomes stable from neutral to positive, suggesting that agents put more effort into customers with negative emotion.

Table 4, Model (4) also corroborates that conversations that begin with customers with negative emotion tend to have more turns relative to neutral (about 3.5 turns more); neutral customers have about 0.7 turns more on average relative to positive emotion customers. For an average conversation of 10 turns, a difference in four turns (the estimated change from negative to positive emotion) is relatively large and also similar in magnitude to that obtained in the linear specification of Table 3.

Altogether, the results suggest two paths through which customer emotion affects agent behavior. First, the agent spends more effort writing to customers with negative sentiment (compared to neutral sentiment), which increases response time. But this mechanism does not explain in full the increase in RT. For customer messages of similar length, the results suggest that RT continues to be longer for customers with negative emotion relative to neutral and positive emotion. One possible explanation for this effect is that agents procrastinate the service of customers with negative emotion, giving them less priority relative to other concurrent customers they are serving. In what follows, we conducted additional analysis to test for this potential explanation.

An increase in RT due to agent's avoidance in serving customers with negative emotion should be predominant during time periods in which the agent is handling several concurrent conversations. In fact, this mechanism cannot operate when the agent is handling a single focal conversation. The idea is then to measure the effect of EMO under situations when there are concurrent conversations versus a single conversation handled by the agent. A dummy variable $NoConcurrent$ is constructed to indicate whether a message was handled during a period with no other conversations assigned to the agent (that is, $Concurrent = 1$). Only 15% of the messages observed in the data have no concurrent cases handled by the agent, reflecting that the service system allocates work in order to keep agents multitasking most of the time. $NoConcurrent$ is added to models (1)–(2) as a

Table 4 Effect of Customer Emotion on Agent Behavior. Emotion is Measured in Three Levels: Negative, Neutral and Positive emotion. The Excluded Level is Neutral. (Outliers Excluded)

	Model (1) $log(RT)$	Model (2) $log(RT)$	Model (3) $log(NumWords)$	Model (4) $NTurns$
$EMO\_negative$	0.118***	0.061***	0.127***	
	(0.0122)	(0.0112)	(0.0110)	
$EMO\_positive$	-0.290***	-0.299***	0.020***	
	(0.0041)	(0.0038)	(0.0037)	
$EMO\_negative_1$				3.474***
				(0.1769)
$EMO\_positive_1$				-0.726***
				(0.1234)
$Concurrent$	0.058***	0.075***	-0.040***	-1.243***
	(0.0026)	(0.0024)	(0.0024)	(0.0369)
$NumInQueue$	0.003***	0.002***	0.002*	0.030***
	(0.0007)	(0.0006)	(0.0006)	(0.0047)
$ConvStage$	0.251***	0.044***	0.464***	
	(0.0043)	(0.0040)	(0.0039)	
$log(NumWords)$		0.447***		
		(0.0015)		
$SrvType$				6.482*
				(3.1572)
$log(CustWords_1)$				-0.417***
				(0.0239)
$IsWeekend$				-0.024
				(0.0417)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.641***	2.255***	3.099***	11.613***
	(0.0071)	(0.0079)	(0.0064)	1.6879
Observations	651,171	651,171	651,171	141,777
R^2 Within	0.002	0.165	0.039	.
R^2 Between	0.017	0.228	0.061	0.010
R^2 Overall	0.008	0.178	0.044	0.003

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

main effect and interacted with EMO; both EMO and its interaction effect are instrumented using $CustSent$ and the respective interaction with $NoConcurrent$. The estimation results are reported in Table 5. Models (1) and (2) show that EMO has a negative and significant effect on RT (similar in magnitude to the main results in Table 3), but that the interaction between EMO and $NoConcurrent$ is not significant. This means that the effect of customer emotion on RT appears to be similar regardless on whether the agent is handing one or multiple cases simultaneously. The lack of significance of the interaction effect *does not support* the avoidance hypothesis, favoring other mechanisms that may explain an increase in RT for customers with negative emotion, such as an increase in the effort required to answer the customer messages or a higher probability of making mistakes (Section 6 provides further discussion on these alternative mechanisms). Note however that one possible reason for the lack of significance is the low precision of the estimates of the interaction effect, with standard errors that are more than one order of magnitude larger relative to the other estimated coefficients. This low precision is a consequence of the low fraction of messages handled with no concurrent cases, an inherent limitation in the context of this study.

The results of Table 5 also suggest an interesting pattern on how multitasking affects RT. Consider the case when $Concurrent$ equals one: the total effect is calculated summing up the coefficients of $NoConcurrent$ and $Concurrent$, which equals 0.25 (approx) for Model (1). When $Concurrent$ increases to two, the effect is twice the $Concurrent$ coefficient, equal to 0.114; for $Concurrent = 3$ the effect is 0.17. This implies a U-shaped effect, similar to what has been reported in other contexts in relation to the effect of workload and multitasking on productivity (e.g. Tan and Netessine (2014) and Kc (2013)). At low levels of workload, agents expand their work to fill in the available time, exhibiting longer RTs. As more workload is assigned, they speed-up by shortening the RT for each message. When agents are overloaded, they become less productive (perhaps due to switching costs among conversations) and RT increases again.

5.2. Effect of Agent Behavior on Customer Emotion

Table 6 shows the results of the models with customer emotion EMO as dependent variable (Models (5) and (6)). Recall this specification uses each message as a unit of analysis and includes fixed effects for the conversation, so the identification is based on variation across turns within a conversation. Two specifications were estimated, including different sets of covariates that measure distinct aspects of agent productivity. The specification reported in the first column corresponds to Model (5), which includes RT as the main covariate. This estimation suggests that doubling RT decreases customer emotion by 0.06, equivalent to less than 0.1 standard deviations, a relatively small effect. Both models (5) and (6) are estimated with Two-Stage Least Squares, where RT is instrumented with the exogenous variables W ($Concurrent$ and $NumInQueue$) in order to isolate the variation of RT that is driven by changes in the agent workload (Section 5.3 discuss results of the estimation without Instrumental Variables. The relevant tables are included in the online appendix). The second specification corresponds to Model (6), including RT, $\log(NumWords)$ and the corresponding $Turn$ number as the main covariates. The results reveal that customer emotion becomes more positive for longer messages: doubling $NumWords$ increases EMO by 0.2. In addition, customer emotion tends to decrease for longer conversations: an increase in 10 turns (equal to

Table 5 Effect of Customer Emotion on Agent Behavior Including Interaction (Outliers Excluded)

	Model (1) $log(RT)$	Model (2) $log(RT)$
EMO	-0.206***	-0.209***
	(0.0028)	(0.0026)
$EMO \times NoConcurrent$	0.104	0.176
	(0.1056)	(0.0967)
$Concurrent$	0.057***	0.075***
	(0.0026)	(0.0024)
$NoConcurrent$	0.188**	0.139*
	(0.0689)	(0.0631)
$NumInQueue$	0.003***	0.002***
	(0.0007)	(0.0006)
$ConvStage$	0.247***	0.040***
	(0.0043)	(0.0040)
$log(NumWords)$		0.446***
		(0.0015)
Constant	3.615***	2.227***
	(0.0070)	(0.0079)
Observations	651168	651168
R^2 Within	.	0.162
R^2 Between	0.018	0.226
R^2 Overall	0.010	0.176

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the average turns in a conversation) reduces customer emotion by 0.16. Furthermore, controlling for these other measures of agent productivity reveals a larger effect of RT on customer emotion: doubling response time decreases EMO by 0.43, which is about half the standard deviation of the dependent variable.

Overall, the results suggest that customer emotion is affected by the different measures of agent productivity, where the predominant effect is a negative effect of RT on customer emotion. The managerial implications of these results is discussed in the next section.

5.3. Sensitivity Analysis and Alternative Specifications

We analyzed several alternative specifications of the models to verify the robustness of the empirical results, which are summarized in this section. All the result tables of this additional analysis are reported in the online appendix.

Models (1)–(4) in Table 3 are estimated with 2SLS instrumenting EMO with an alternative sentiment measure, in order to mitigate attenuation bias due to measurement error. For robustness, the same specifications were estimated with Ordinary Least Squares (OLS), without instruments (Table EC.2). The results reveal a negative effect of EMO on RT, which is statistically significant but smaller in magnitude (coefficient is approx. -0.1 compared to -0.2 in Table 3). Similarly, in

Table 6 Effect of Agent Behavior on Customer Emotion (Outliers Excluded)

	Model (5) EMO	Model (6) EMO
$log(RT)$	-0.062***	-0.427***
	(0.0145)	(0.0403)
$ConvStage$	0.896***	1.181***
	(0.0057)	(0.0079)
$log(NumWords)$		0.200***
		(0.0185)
$Turn$		-0.016***
		(0.0003)
Constant	0.066	0.794***
	(0.0524)	(0.0943)
Observations	586458	586458
R^2 Within	0.095	.
R^2 Between	0.033	0.016
R^2 Overall	0.077	0.033

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model (3) the effect of EMO on $NumWords$ is smaller in magnitude and not statistically significant. For model (4), with $NTurns$ as dependent variable, the coefficient changes from -1.686 to -0.248 (p-value $<$ 0.001). Overall, these results are consistent with attenuation bias due to imprecise measurement of customer emotion, which can be corrected with the IV estimation proposed using an alternative sentiment measure as instrument.

Our analysis uses SentiStrength as the main measure of customer emotion. Additional specifications were estimated using the alternative measure CustSent as the main measure of emotion, and using SentiStrength as IV (Table EC.3). The results were similar in terms of sign, magnitude and statistical significance. In addition, we also estimated models (1)–(4) with and without log transformation for $NumWords$ and $log(NTurns)$: the results were similar in terms of the signs, magnitude and statistical significance (Table EC.4).

Recall that the results from Table 3 are based on a sample without outliers. The same models were estimated with all the observations, including the outliers (Table EC.5). Overall, the conclusions obtained from these results are similar. The coefficients associated to EMO in models (1) and (2) continue to be negative, in the order of -0.3. For model (3), the effect of EMO on $NumWords$ becomes negative and significant, with a point estimate of -0.024. As discussed previously, the additional analysis reported in Table 4 showed that the effect of EMO on $NumWords$ appears to be non-linear, suggesting that the model with linear EMO is mispecified and less robust. This may explain why the EMO coefficient in the linear specification is sensitive to the definition of the sample (Table EC.6). In Model (4), with $NTurns$ as dependent variable, the coefficient on EMO_1 is similar, equal to -1.678.

Additional analysis was done to evaluate the robustness of models (5) and (6) (main results reported in Table 6), where the dependent variable is customer emotion. Recall that these models are estimated with Instrumental Variables to address the endogeneity of RT, which is potentially correlated with unobservable factors associated to the quality of the response. The same models were estimated without Instrumental Variables using OLS (Table EC.7). The coefficient associated with $\log(RT)$ flips from negative to positive, with a point estimate close to 0.02 (with p-value $<$ 0.001). This is consistent with the endogeneity bias that was conjectured: because RT is likely to be positively correlated with unobservable quality that is part of the error term, this generates a positive bias in the estimated coefficient of RT. Instrumenting RT with exogenous factors associated to agent workload helps to correct this bias.

Models (5) and (6) were also estimated replacing EMO with the alternative $CustSent$ measure (Table EC.8). The results are similar for model (6), but for model (5) the effect of RT was not significant. The models were also estimated including the outliers in the sample and the results were similar (Table EC.9).

Overall, the sensitivity analysis provides further support of the estimation results, showing that they are robust to alternative specifications.

6. Discussion and Managerial Implications

In this section we first discuss in more depth our results (§6.1) and then deliberate on the implication of those results on operational decisions in contact centers (§6.2).

6.1. Discussion of Empirical Results

Our results show the effects of customer emotion on agent behavior, and the reverse effect of agent behavior on customer emotion (Tables 3–6). We found that negative customer emotion, a case of high *emotional load*, hampers agent efficiency as evident in longer agent RT and the larger number of turns it takes to complete the service thus supporting—supporting Hypotheses 1 and 5. We find that a central mechanism through which emotional load impacts performance is *agent effort* as manifested in the number of words agents write following a customer message that is emotionally demanding.

We find that expressions of customer negative emotion increase agent effort (supporting Hypothesis 3), and that when an agent writes more text, RT increases (supporting Hypothesis 9). A proxy for the total effort required to complete a case can be calculated by multiplying the number of words per turn and the number of turns. Based on this measure, the results suggest that negative chat requires 32% *more* words compared to a neutral chat (363 compared to 274[1]), while a positive

[1] The average number of words in Neutral message is 26.88.

chat requires a total of 15% *less* words than neutral chat due to the decrease in the number of turns in chats (Model 4 in Table 4). When considering only the effect of a single turn, positive customer emotion reduces RT despite increased agent effort per message written. This is consistent with the mechanism where positive emotions enhance employee motivation and therefore her productivity (Hypothesis 1). However, effort as measured by the number of words may not tell the whole story. Agent efforts outside of the chat platform (e.g., in the Customer Relationship Management software) are absent from our data. We capture such "hidden" effort via the main effect of EMO on RT and call for future research to replicate our results with different proxies of effort, other than the number of words agents use in service.

Interestingly, agent effort explains only a part of the variance in agent performance following expressions of customer emotion (Table 3).Two additional explanations can clarify the effect of emotional load on employee performance. First, employees make more mistakes when exposed to negative emotion of others (Rafaeli et al. 2012) thus increasing the number of turns it take to complete the service. Unfortunately, our data does not allow us to measure agent mistakes. We therefore call for future research to examine the possible mediating role of mistakes in decreased performance following exposure to emotional load. Second, agents may avoid customers that present high emotional load by providing service to other (concurrent) customers. The analysis comparing the effect of emotion in cases with and without concurrent customers served by the same agent show that the effect is similar in both cases, suggesting that this "avoidance" mechanism is less likely to explain the observed effect.

The estimates suggest that the effects of emotional on agent behavior are large relative to other workload factors. A decrease in emotion of one point is equivalent to increase the number of concurrent customers handled by the agent from 1 to 4, which is a large change (see Model (2) in Table 3). The effect on the number of words is similar in magnitude (Model (3) in Table 4).

Looking at the reverse direction of influence, our results show that longer RT and higher number of turns *reduce* customer emotion (Table 6), thus supporting Hypotheses 8 and 10. Additionally, we found that as agents put more effort (increase $NumWords$), customer emotion improves supporting Hypotheses 9.

6.2. Managerial Implications

The fact that customer emotion impacts agent behavior and that agent behavior impacts customer emotion suggests that emotional load should be monitored and taken into account in operational decisions. This section discusses some prescriptions for the design and control of service systems that are subject to the effects of emotional load. This is even more important considering findings that suggest that customer emotions reflect customer satisfaction (Yom-Tov et al. 2018) and the connection of the latter to organization profitability.

• **Productivity targets, system design and staffing.** The results provide a "call for awareness" that emotional load exists, varies within a service episode, and impacts agent performance. A standard approach is to consider service time and case characteristics as the key dimensions of load, but our work suggests that customer emotion is another important factor that should be considered. When agents deal with more negative customers they should be expected to need more time to solve the customer issues and to coup with customer emotions. To evaluate the total effects of emotion, it is useful to compare the agent time required to handle angry (negative), neutral, and happy (positive) customers. Define total throughput time by multiplying the average agent RT per turn by the average number of turns in a chat. The total throughput time of an angry customer is 15.9 minutes (1.34 minutes times 11.9 turns); compared to 11.1 minutes of a neutral customer and 7.5 minutes of a happy one. This analysis suggests that the total amount of throughput time associated with an angry customer is 43% larger than the one associated with a neutral one. Many contact centers measure their employee productivity by the numbers of calls per hour an agent handles (average concurency divided by total throughput time). They should be aware that an agent can serve 12.6 neutral customers per hour but only 8.8 angry ones. Hence, the evaluation of service agents or teams who encounter a high proportion of angry customers (for example customer retention teams) should be based on adjusted targets of conversations per hour. This is important if a contact center is considering a design change to incorporate Skill-Based routing design (i.e. that each customer group is served by a separated agent-skill group).

Another way to think about the implication of emotional load is to consider how variations in customer mix impact the offered load, which is equivalent to the amount of staffing required to handle the arriving customer workload. We present in Table 7 a comparison between the offered load (calculated by the arrival rate[2] times total throughput times divided by average concurency) of the current mix of emotional messages in our contact center vs. the offered load that the agents will need to handle if 10% of the messages transformed from being neutral to negative for some reason. This could happen if, for example, the company has some kind of failure with one of its products or services. This change in customer behavior increases the amount of agents needed to handle customer issues by 4.6% and the amount of text written per day by 3.3% (assuming arrival rate is the same for both scenarios). As a conclusion, this analysis suggest that customer emotion is an important factor that should be accounted for in staffing decisions.

• **Counterfactual analysis to analyze the impact of emotional load on service quality.** Most organizations do not monitor customer emotions and do not adjust staffing to match the variation in customer sentiment. Here we would like to calculate the impact of an increase in emotional

[2] Arrival rate data is given in Appendix EC.3.

Table 7 Comparison of Working Hour Associated with Different Mix of Message Sentiment

Emotion Type	Base Case Message percentage	Offered Load	Effort (NumWords)	Alternative Case Message percentage	Offered Load	Effort (NumWords)
Positive	29%	14.7	63,808	29%	14.7	63,808
Neutral	63%	47.1	162,812	53%	39.6	136,969
Negative	8%	8.6	27,358	18%	19.3	61,556
Total	100%	70.4	253,978	100%	73.7	262,333

load on performance level, in case the company does not change staffing. We use the same scenario presented in Table 7. We use a simulation model that was calibrated to the operation of contact centers developed by Castellanos et al. (2019). It is a version of an Erlang-A model that takes into account unique contact center features such as silent abandonment. For this counterfancual analysis, we estimated the simulation parameters using the data of February 2017. The simulation assumes that customers arrive to the contact center according to a non-homogeneous Poisson process with rate $\lambda_{d,t}$ ($\lambda_{d,t}$ is the arrival rate at day d and hour t). The customer are served by $n_{d,t}$ statistically identical agents, with average concurency of c. Therefore, the number of service slots available at time (d,t) is $cn_{d,t}$. If there is no available slot, the customer wait in a FCFS queue. The customer has finite patience and assumed to be Exponentially distributed with rate $theta$, which was estimated using the methodology developed in Yefenof et al. (2018), that takes into account the fact that customer waiting time in chat systems is censored both from the right (by the offered wait) and from the left (by the fact that sometimes customers abandon the service without exiting the queue—they don't close the chat window but disappear. For more details about this silent abandonment phenomena and its implication see Castellanos et al. (2019)). In our data $\theta = 0.5$, and 70% of the customers indicates their abandonment in real time (30% abandon silently). Service times are assumed to be exponentially distributed with rate μ. Note that μ in this simulation is one the divided by the throughput time of a conversation and equal to $\mu = 0.075$; in the counterfactual scenario with more negative emotion customers, μ was adjusted so that the throughput time was 4.6% longer (as suggested by our empirical results).

The simulation predicts that the 10% change of neutral lines to negative lines increase the probability of abandonment by 2% and increase the expected waiting time by two minutes.

- **Routing policies designed to achieve: load balancing or specialization.**

Emotional load should also have impact on work allocation (routing) decisions. In our data, agents usually treat up to three customers at the same time (on average 2.3 customers simultaneously). But the load created by three angry customers differs dramatically from the load created by three happy customers. Specifically, treating three neutral customers messages is equivalent (in terms of workload) to treating only 2.4 angry messages or 3.7 positive messages. We suggest that like other measures of workload, emotional workload could be used in the design of dispatching rules commonly used in contact centers, *dynamically* adjusting the workload of agents based on real-time assessments. The sentiment analysis tool used in this work allows for real-time monitoring of emotional load during service conversations. Previous research showed that there is a clear trend of sentiment within a conversation (Yom-Tov et al. 2018): customer sentiment usually starts negative, then becomes neutral and transforms to positive towards the end of the conversation. This positive trend is captured in our analysis by the variable *ConvStage* that monitors the conversation progress. Interestingly, this trend is steeper when customers report that their problem was solved and that they are satisfied with the service as indicated in post-service surveys. Unfortunately, we do not have access to customer survey responses in our data, therefore refer the readers to (Yom-Tov et al. 2018). Although most of the customers start by expressing negative emotions, some of them will express more positive emotions throughout the conversation while others will remain unhappy. We suggest designing a routing policy that would *balance* both offered load as well as emotional load. The idea is that when a new conversation arrives it will be assigned to an agent that has the least emotional load. Therefore, only when the real-time assessment of the emotions of the currently assigned customers identifies that the customer transformed from being negative to positive state the agent load will decrease and enable new allocation of customers to her. Such a policy will dynamically allocate more capacity to agents that handle customers who consistently express negative emotion. This dynamic allocation which allows more agent time to negative customers is expected to improve customer emotions since agents can pay more attention to them, and therefore, may also improve overall customer satisfaction. This idea draws its intuition from Armony and Ward (2010), Mandelbaum et al. (2012), who suggest adoption of allocating policy that is fair from the agent perspective (Carmeli et al. 2018).

In addition, in some contact centers customers write their inquiry before entering the queue (Castellanos et al. 2019). In such cases, we can assess the emotional load expected by that customer inquiry in real-time before assigning the new conversation to an agent and using the measure of emotional load we can also predict that customer needs. Model 3 supports the claim that this is indeed possible by showing that one can predict the number of turns that a chat will need using the customer sentiment of his first turn. This information can be used for designing a *"sentiment-based routing"*, a mechanism that is analogous to skill-based routing. This routing mechanism will assign an emotional call to appropriate agent group (e.g. customer retention team) that received training of how to deal with agent anger.

- **Prioritization.** Our results highlight that customer RT impact customer emotions. Therefore, operational policies that will reduce agent RT will improve customer emotions. This can be done in the following way: sentiment engines can be designed to provide real-time monitoring of customer sentiment, and alert managers and agents of problematic situations (e.g. when the sentiment of a customer dropped below a specific threshold). Since agents handle multiple customers in parallel, they might miss customers expressions of negative emotion while they are interacting with other customers. Real-time monitoring can increase agents awareness by alerting them when an escalation in negative emotion occurs. These alerts will enable agents to *prioritize* angry customers, reduce their RT, and improve their satisfaction. Moreover, managers can use these alerts to identify extreme negative sentiment cases, and to provide agents with relevant assistance. This idea is now being implemented in one of the companies working with the LivePerson platform. In addition, our results highlight how important it is for the agent to communicate his effort by writing longer text. If agents will be more aware of the current state of the customer (by the suggested alerts), and react by communicating their effort better, customer emotion are expected to improve.

7. Conclusions

Research to date provides ambiguous predictions regarding the effects of expressed customer emotion on agent behavior. Our findings reconcile conflicting predictions and show that deterioration in customer emotion hampers agent performance-related behaviors: agents respond slower, write more words, and need more turns to complete a service interaction when customers express negative emotion. These findings suggest that negative customer emotions create a burden on agents while positive emotions act as a source of motivation (Bakker and Demerouti 2007). Our analyses are based on operational and objective measures of agent behavior and of customer emotion in real service interactions, and thus overcome limitations of past research. Previous research relied almost solely on experimental manipulations with small samples and self reported emotions, affording limited managerial insights.

Our findings support the idea that the complexity that customers bring to a service system, in terms of the problems and the emotions they present, is critical for understanding and predicting agent work performance (Weiss and Cropanzano 1996). Yet, we acknowledge that our study could not consider the effects of discrete emotions (i.e., anger, frustration, delight), although this is what research in Organizational Behavior advocates (Lazarus and Cohen-Charash 2001). We hope that future developments in Natural Language Processing will allow for analyses in higher granularity of discrete emotions.

We introduce a new position for customer emotion in service—that of a potential source of load. This is in contrast to traditional Operations Management views, where customer emotion is treated as an outcome. The implicit assumption of past research was that customer happiness depends on their evaluation of the quality of service. We show, however, that customer emotions are also a factor that determines the efficiency of service; suggesting that the concept of load, as traditionally studied in Operations Management, actually comprises multiple aspects, and that emotional load is an important construct to account for in planing models. This view of load accounts for pressures beyond the mere presence of a customer, and is based on factors inherent to the nature and content of individual service interactions.

Our results show that emotional load creates “micro-level influences”, that occur at the level of a single message within the conversation between a specific employee and a specific customer. We theorize and show empirical effects of emotional load that goes beyond multitasking and queue length effects. Our analyses of a large data-set of conversations between agents and customers, show empirical measurements of this type of load, and document its influence on critical Operations Management parameters of agent RT, agent effort, and the number of turns it take to complete a conversation.

We call for researchers and practitioners to view customer emotion as data that can aid them in designing service systems. Emotions provide information (data) about a social situation and the actors in it (van Kleef 2015). To this day, these data served only the service dyad: an agent and a customer. This dyad is engaged in co-production of value; both actors invest effort to resolve a specific issue. The ratio of the effort between the service interaction partners is dependent on context. If a customer requests easy-to-get information, the ratio of effort will be close to 1. In contrast, if a customer has a complicated request, or if the customer creates high emotional load, the agent will likely need to invest more effort than the customer. As Roels (2014) showed, one can improve service system efficiency by considering the effort ratio and route customers to adequate service channels based on it. Our results show that service systems should use customer emotion as data that will aid them in allocating customers to agents or other service channels that fits thier needs.

The type of data we use in the current paper is increasingly available in service organizations (i.e., full documentation of service). We highlight the opportunities that such data, coupled with automated sentiment analysis tools create for studying service delivery (Rafaeli et al. 2017) and improving the operations of service operations. From a managerial perspective, our analyses suggest the importance of incorporating real time monitoring of customer emotions being handled by service agents. Beyond the technical count of the number of customers in the service system, service operations need to acknowledge the dynamics that customers bring to the system. This includes the types of problems that customers raise, the verbosity with which they communicate their problems, and the emotions that they attach to this communication. Failing to recognize such customer induced states can lead to inaccurate planning models and suboptimal service management.

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EC.1. Precision and Recall of Sentiment Analysis Tools (Yom-Tov et al. 2018)

Table EC.1 Comparing four models in detecting emotion in customer messages.

Emotion class	Model	Precision	Recall	F_1	$F_{0.5}$
Negative	SentiStrength	0.494	0.216	0.300	0.393
	CustSent	0.719	0.236	0.355	0.51
	Stanford	0.335	0.509	0.404	0.36
	LIWC	0.479	0.115	0.186	0.294
Positive	SentiStrength	0.813	0.677	0.739	0.781
	CustSent	0.866	0.569	0.687	0.784
	Stanford	0.546	0.339	0.418	0.486
	LIWC	0.491	0.717	0.583	0.524

EC.2. Sensitivity Analysis and Alternative Specifications Results

Table EC.2 Effect of Customer Emotion on Agent Behavior (Outliers Excluded); OLS with no IVs

	Model(1) $log(RT)$	Model(2) $log(RT)$	Model (3) $log(NumWords)$	Model (4) $NTurns$
EMO	-0.096***	-0.097***	0.001	
	(0.0016)	(0.0014)	(0.0014)	
EMO_1				-0.248***
				(0.0296)
$Concurrent$	0.056***	0.073***	-0.040***	-1.243***
	(0.0026)	(0.0024)	(0.0024)	(0.0366)
$NumInQueue$	0.003***	0.003***	0.002*	0.030***
	(0.0007)	(0.0006)	(0.0006)	(0.0046)
$ConvStage$	0.168***	-0.040***	0.468***	
	(0.0039)	(0.0036)	(0.0035)	
$log(NumWords)$		0.446***		
		(0.0014)		
$log(CustWords_1)$				-0.326***
				(0.0211)
$IsWeekend$				-0.013
				(0.0416)
$SrvType$				6.199*
				(3.1524)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.634***	2.246***	3.112***	11.106***
	(0.0070)	(0.0078)	(0.0063)	(1.6637)
Observations	651168	651168	651168	141777
R^2 Within	0.010	0.172	0.040	0.011
R^2 Between	0.020	0.237	0.058	0.017
R^2 Overall	0.010	0.187	0.044	0.003

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.3 Effect of Customer Emotion on Agent Behavior (Outliers Excluded); Using $CustSent$ as the Main Measure of Customer Emotion

	Model(1) $log(RT)$	Model(2) $log(RT)$	Model (3) $log(NumWords)$	Model (4) $NTurns$
$CustSent$	-0.184***	-0.185***	0.002	
	(0.0030)	(0.0027)	(0.0027)	
$CustSent_1$				-0.704***
				(0.0837)
$Concurrent$	0.058***	0.075***	-0.040***	-1.235***
	(0.0026)	(0.0024)	(0.0024)	(0.0365)
$NumInQueue$	0.003***	0.003***	0.002*	0.029***
	(0.0007)	(0.0006)	(0.0006)	(0.0047)
$ConvStage$	0.273***	0.064***	0.467***	
	(0.0047)	(0.0043)	(0.0042)	
$log(NumWords)$		0.447***		
		(0.0014)		
$log(CustWords_1)$				-0.353***
				(0.0211)
$IsWeekend$				-0.018
				(0.0412)
$SrvType$				5.944
				(3.1207)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.584***	2.194***	3.112***	11.142***
	(0.0070)	(0.0079)	(0.0064)	(1.6607)
Observations	651168	651168	651168	141777
R^2 Within	0.010	0.173	0.040	0.015
R^2 Between	0.028	0.241	0.058	0.016
R^2 Overall	0.013	0.186	0.044	0.004

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.4 Effect of Customer Emotion on Agent Behavior (Outliers Excluded); using $NumWords$

	Model(1) $log(RT)$	Model(2) $log(RT)$	Model (3) $NumWords$	Model (4) $NTurns$
EMO	-0.206*** (0.0028)	-0.223*** (0.0026)	1.452*** (0.0910)	
EMO_1				-1.615*** (0.108)
$Concurrent$	0.057*** (0.0026)	0.077*** (0.0024)	-1.671*** (0.0851)	-1.263*** (0.0369)
$NumInQueue$	0.003*** (0.0007)	0.003*** (0.0007)	0.036 (0.0229)	0.029*** (0.0047)
$ConvStage$	0.246*** (0.0043)	0.055*** (0.0040)	16.218*** (0.1376)	
$NumWords$		0.012*** (0.0000)		
$CustWords_1$				0.000 (0.0009)
$IsWeekend$				-0.013 (0.0416)
$SrvType$				6.065 (3.1525)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.616*** (0.0070)	3.280*** (0.0066)	28.509*** (0.2266)	10.286*** (1.6768)
Observations	651168	651168	651168	141777
R^2 Within	.	0.141	0.042	.
R^2 Between	0.018	0.234	0.079	0.009
R^2 Overall	0.009	0.158	0.050	0.003

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.5 Effect of Customer Emotion on Agent Behavior (Outliers Included)

	Model(1) $log(RT)$	Model(2) $log(RT)$	Model (3) $log(NumWords)$	Model (4) $NTurns$
EMO	-0.343***	-0.332***	-0.024***	
	(0.0031)	(0.0030)	(0.0023)	
EMO_1				-1.677***
				(0.0638)
$Concurrent$	0.098***	0.112***	-0.031***	-1.153***
	(0.0030)	(0.0028)	(0.0022)	(0.0337)
$NumInQueue$	0.004***	0.003***	0.002***	0.030***
	(0.0008)	(0.0008)	(0.0006)	(0.0043)
$ConvStage$	0.280***	0.016***	0.570***	
	(0.0048)	(0.0046)	(0.0035)	
$log(NumWords)$		0.462***		
		(0.0016)		
$log(CustWords_1)$				-0.299***
				(0.0196)
$IsWeekend$				0.0171
				(0.0385)
$SrvType$				5.612
				(3.1187)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.442***	2.018***	3.083***	10.716***
	(0.0079)	(0.0089)	(0.0058)	(1.5582)
Observations	825577	825577	825583	162362
R^2 Within	.	0.115	0.050	.
R^2 Between	0.038	0.225	0.114	0.023
R^2 Overall	0.016	0.137	0.055	0.005

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.6 Effect of Customer Emotion on Agent Behavior. Emotion is Measured in Three Levels: Negative, Neutral and Positive emotion. The Excluded Level is Neutral. (Outliers Included)

	Model(1) $log(RT)$	Model(2) $log(RT)$	Model (3) $log(NumWords)$	Model (4) $NTurns$
$EMO\_negative$	0.183***	0.121***	0.133***	
	(0.0143)	(0.0134)	(0.0105)	
$EMO\_positive$	-0.525***	-0.512***	-0.028***	
	(0.0046)	(0.0043)	(0.0034)	
$EMO\_negative_1$				3.271***
				(0.1638)
$EMO\_positive_1$				-0.907***
				(0.1140)
$Concurrent$	0.100***	0.114***	-0.031***	-1.154***
	(0.0030)	(0.0028)	(0.0022)	(0.0337)
$NumInQueue$	0.004***	0.003***	0.002***	0.029***
	(0.0008)	(0.0008)	(0.0006)	(0.0044)
$ConvStage$	0.315***	0.050***	0.574***	
	(0.0049)	(0.0047)	(0.0036)	
$log(NumWords)$		0.463***		
		(0.0016)		
$log(CustWords_1)$				-0.371***
				(0.0222)
$IsWeekend$				0.007
				(0.0386)
$SrvType$				5.868
				(3.1237)
$ShiftTime$				Included
$HourOfDay$				Included
Conversation Fixed Effect	Included	Included	Included	
Agent Fixed Effect				Included
Constant	3.481***	2.058***	3.075***	9.734
	(0.0080)	(0.0090)	(0.0059)	(7.0542)
Observations	825577	825577	825583	162362
R^2 Within	0.003	0.120	0.049	.
R^2 Between	0.039	0.230	0.112	0.022
R^2 Overall	0.017	0.140	0.054	0.005

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.7 Effect of Agent Behavior on Customer Emotion (Outliers Excluded); OLS with no IVs

	Model (5) EMO	Model (6) EMO
$log(RT))$	0.019***	0.022***
	(0.0013)	(0.0014)
$ConvStage$	0.842***	1.129***
	(0.0035)	(0.0063)
$log(NumWords)$		-0.015***
		(0.0014)
$Turn$		-0.015***
		(0.0003)
Conversation Fixed Effect	Included	Included
Constant	-0.208***	-0.205***
	(0.0050)	(0.0051)
Observations	739425	739425
R^2 Within	0.102	0.107
R^2 Between	0.044	0.040
R^2 Overall	0.084	0.082

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.8 Effect of Agent Behavior on Customer Emotion (Outliers Excluded); using $CustSent$ as the Main Measure of Customer Emotion

	Model (5) $CustSent$	Model (6) $CustSent$
$log(RT)$	0.027	-0.275***
	(0.0140)	(0.0375)
$ConvStage$	1.030***	1.397***
	(0.0055)	(0.0074)
$log(NumWords)$		0.137***
		(0.0172)
$Turn$		-0.019***
		(0.0003)
Conversation Fixed Effect	Included	Included
Constant	-0.366***	0.300***
	(0.0506)	(0.0878)
Observations	586456	586456
R^2 Within	0.146	0.076
R^2 Between	0.067	0.041
R^2 Overall	0.121	0.082

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table EC.9 **Effect of Agent Behavior on Customer Emotion (Outliers Included)**

	Model (5) *EMO*	Model (6) *EMO*
$log(RT)$	-0.056***	-0.328***
	(0.0100)	(0.0256)
$ConvStage$	0.875***	1.114***
	(0.0044)	(0.0068)
$log(NumWords)$		0.163***
		(0.0125)
$Turn$		-0.015***
		(0.0003)
Conversation Fixed Effect	Included	Included
Constant	0.055	0.528***
	(0.0354)	(0.0558)
Observations	725805	725805
R^2 Within	0.090	.
R^2 Between	0.024	0.014
R^2 Overall	0.075	0.032

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

EC.3. Arrival Rate

In this section we provide additional data needed for the calculations of the impact of our results on offered load. Table EC.10 provide a typical pattern of customer arrival rate per working hour in our data.

Table EC.10 **Arrival Rate during a Working Day**

Hour	λ
9	62.45
10	67.6
11	63.75
12	67.25
13	68.9
14	69.05
15	86.25
16	90.2
17	68.1
18	63.5
19	59.35
20	65.5
21	57.95
22	53.65