The effect of customer emotion and work demands on employee unscheduled breaks: An investigation of chat-based customer service

Research Thesis

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Abstract

The current study examines the influence of customer emotions and work demands on service employees' withdrawal behaviors. Available research on such effects relies mainly on self-report measures of relatively small samples, and looks mostly on more severe withdrawal (absenteeism and quitting jobs). We examine chat-based service, which is unique in its great potential for automated analyses of objective measures from large samples. We study service chats conducted through the LivePerson Inc. platform (https://www.liveperson.com), and examine the influence of work demands and customer emotions (identified using a home-grown sentiment analysis tool, adapted for chat data). The dependent variable of the study is employee *minor withdrawal behaviors*, which are subtle withdrawal behaviors exhibited during the work shift, and we define as spontaneous, unscheduled employee breaks. With a sample of 3,084 time intervals and 835 breaks, we find that: (a) Work demands increase the likelihood and duration of employee withdrawal; (b) Customer positive emotions increase the likelihood of employee withdrawal; (c) Customer negative and positive emotions moderate the effect of work demands on duration of withdrawal behaviors; when customers express high negative emotions, higher work demands lead to longer breaks. In contrast, when customers express high positive emotions, the effect reverses, and higher work demands lead to shorter breaks. Our findings offer strong empirical support for the Job Demands-Resources model, with real-life non-obtrusive measures. The findings highlight the importance of attention to work demands and to customer emotions and open new directions for implementing sentiment analysis in designing chat platforms (e.g., determining staffing of employees and routing of customers).

List of Abbreviations and Notations

Abbreviation/ Notation	**Explanation**
i	Specific time interval
j	Specific employee
e	Emotion valence
n	Number of message
N_Read	Number of words employee read
N_Wrote	Number of words employee wrote
N_Chats	Number of chats employee handled
M_Concurrent	Average number of concurrent chats
Work_Demands	Employee work demands
Cus_Neg_Emo	Customer negative emotions
Cus_Pos_Emo	Customer positive emotions
Shift_Start	Shift start
Rest_Time	Rest time
Queue_Wait	Queue wait
Emp_Wait	Employee wait
M_Chat_Dur	Average chat duration
M_Emo_Cust	Average emotion in chat
P_Emo_Cust	Proportion of emotional chats
Col_Num	Number of colleagues
Skill	Skill of the employee- service vs. sales
Shift	Shift- morning vs. evening
Hour	Hour of day
Day	Day of week
Break_Binary	Whether an employee took a break or not
Break_Dur	Duration of an employee's break

Introduction

Emotions are an integral part of our everyday lives. They emerge as a reaction to appraisals of different stimuli (Moors, Ellsworth, Scherer, & Frijda, 2013), convey social information (Van Kleef, 2009) and are essential for proper social functioning (Niedenthal & Brauer, 2012). Expressions of emotions were found to have a profound influence on the interaction partner (Van Kleef, 2009; Van Kleef, Berg, Heerdink, & Heerdink, 2014), his behavior (Van Kleef & Côté, 2007) and attitudes (Van Kleef et al., 2014)

In customer service, emotions have a strong influence on customer's outcomes, such as customer intentions, behaviors, satisfaction and loyalty (DeWitt, Nguyen, & Marshall, 2008; Hennig-Thurau, Groth, Paul, & Gremler, 2006; Mattila & Ro, 2008; Vinagre & Neves, 2008). Moreover, customer emotions have an influence on employee behaviors (Grandey, Dickter, & Sin, 2003), cognitions (Mo Wang et al., 2013) and performance (Rafaeli et al., 2012). For example, a research found that customer mistreatment (e.g., yelling at the employee, refusing to listen to the employee) led to more rumination among employees, which in turn resulted in higher negative mood (Mo Wang et al., 2013)

Emotions are argued to prevail in customer service interactions, and also in computer-mediated interactions (For a review, see Derks, Fischer, & Bos, 2008). Research has found that individuals are able to communicate their positive and negative emotions via verbal and non-verbal strategies in text-based interactions (Hancock, Landrigan, & Silver, 2007; Harris & Paradice, 2007). Technology nowadays enables automatic detection of emotions through sentiment analysis tools, such as LIWC (Tausczik & Pennebaker, 2010) and SentiStrength

(Thelwall 2013; For reviews of different sentiment analysis tools, see Gonçalves, Araújo, Benevenuto, & Cha, 2013; Serrano-Guerrero, Olivas, Romero, & Herrera-Viedma, 2015).

Sentiment analysis tools can easily explore a large amount of messages and detect expressions of positive or negative emotions. This technology offers a great opportunity for the research of emotions, since it allows for a non-obtrusive and objective measurement of emotions in large-scale data. The current study will use this innovative technology in order to complement the research on emotions in customer-service contexts. The current study will use a home-grown sentiment analysis tool in order to identify the influence of customer emotions on employee behaviors. We will focus specifically on employee withdrawal behaviors, since they entail major economic outcomes for organizations.

Withdrawal Behaviors

The construct of organizational withdrawal behavior is composed of two components: work withdrawal and job withdrawal. Work withdrawal are behaviors that employees do in order to avoid some aspects of their work role, or in order to minimize the time they spend on specific work tasks, while still maintaining their current organizational and work-role memberships—for example, missing meetings and tardiness. On the other hand, job withdrawal represents employees' behaviors that are aimed to removing themselves from the organization, such as turnover (Hanisch & Hulin, 1991).

A continuum of withdrawal behaviors was suggested by Sagie, Birati, and Tziner, (2002). The continuum starts with relatively mild behaviors, such as withholding effort at work, meaning being present but not carrying one's duties to the best of his or her abilities.

It continues with behaviors that retreats from the organization while maintaining organizational and job-role memberships, such as lateness or absenteeism. In the end of the continuum there are the most “severe” withdrawal behaviors, which represent a “full withdrawal”, such as turnover, where employees terminate their membership in the organization (Birati & Tziner, 1996; Hanisch & Hulin, 1990, 1991; Sagie et al., 2002).

Withdrawal behaviors are highly frequent in organizations. For example, in a study conducted in Ohio (Bennett & Robinson, 2000), the researchers randomly sent letters to individuals, asking them to indicate the extent to which they engaged in a list of 24 deviant workplace behaviors in the previous year. Forty-seven percent of the individuals reported daydreaming instead of working at least once, 33% reported being late to work, 31% reported intentionally working slower than they could work and 52% reported taking longer or additional breaks than is acceptable. In general, service organizations are known for their high turnover rate. For example, *The Global Call Centre Report* noted a turnover rate of 20% per year in a typical call center (Holman, Batt, & Holtgrewe, 2007).

It is highly important that organizations attend to withdrawal behaviors, even to the relatively mild ones, since according to the “Progression Of Withdrawal” model (Berry, Lelchook, & Clark, 2012; Johns, 2001), withdrawal behaviors are related in a progressing fashion. The model suggests that mild withdrawal behaviors are predictors of more severe and salient withdrawal behaviors; for example, occasional lateness can predict future absenteeism. According to this model, mild withdrawal behaviors should be considered as warning signs of possibly more severe withdrawal behaviors in the future. Moreover, interventions aimed at eliminating mild withdrawal behaviors may affect also more serious withdrawal behaviors, so by addressing mild behaviors, organizations can prevent escalation into severe withdrawal behaviors (Berry et al., 2012).

Withdrawal behaviors are extremely important to diminish as they entail major economic outcomes for the organization, which can range from mild consequences such as overpay to severe outcomes such as the loss of customers (Birati & Tziner, 1996; Sagie et al., 2002). Withdrawal behaviors may also entail motivational consequences such as hampered team morale (Sagie et al., 2002). An employee whose coworkers exhibit high levels of withdrawal behaviors is also likely to withdraw from work, meaning that withdrawal behaviors of one person can diffuse to others and accrue high costs for the organization (David, Avery, Witt, & McKay, 2015; Eder & Eisenberger, 2007; Felps, Mitchell, Lee, & Harman, 2009; Johns, 1997; Sagie et al., 2002).

Sagie, Birati and Tziner (2002) included in their model the psychological and financial results of the progression in the continuum and estimated the costs of the mutual interpersonal influences within the work-team. Since withdrawal behaviors can escalate and become more and more severe, and therefore more costly to the organization, there is an extremely high need to identify the causes or precursors to these behaviors and to try to decrease their frequencies. Thus, withdrawal behaviors must be addressed by managers in order to reduce the costs and risks they present for organizations (Sagie et al., 2002).

One type of withdrawal behavior that did not get a lot of attention in the literature is *minor withdrawal behavior* (Koslowsky, 2009). These behaviors are described in the beginning of the continuum of withdrawal behaviors. They represent actions that are exhibited by employees in organizations and can be considered as withdrawal behaviors, although employees allegedly show up at work on time but do not use their time and resources properly. This group of withdrawal behaviors includes behaviors such as daydreaming, surfing the Internet for personal reasons and taking long lunch breaks (Bolino, Long, & Turnley, 2015; Koslowsky, 2009; Laczo & Hanisch, 1999; Liao, Chuang, & Joshi, 2008). For example, there is evidence that customer service employees hang up on customers in order to obtain extra rest time, while still maintaining a required level of performance (Brown et al., 2005).

Minor Withdrawal Behaviors might be invisible to management or seem negligible since they are quite subtle, occur in an acceptable framework, and are less explicit than other withdrawal behaviors, but this is misleading. Like other types of withdrawal behaviors, minor withdrawal behaviors can be contagious. For example, if coworkers see that an employee takes a longer lunch break and is not being punished for it, they may wish to act the same, especially if there are no clear sanctions. Moreover, it was suggested that *minor withdrawal behaviors* can progress to other, more advanced withdrawal behaviors, such as lateness or absenteeism (Koslowsky, 2009). In contrast to other types of withdrawal behavior, *minor withdrawal behaviors* are much more difficult to record and measure in an objective and systematic way. This is probably why, despite their potential costs for organizations, the literature on this type of withdrawal behavior is rather scarce.

Our study will contribute to this field of research by focusing on predicting the likelihood and duration of a specific type of *minor withdrawal behavior*—employees taking short spontaneous unscheduled breaks during their shift. We consider short breaks rather than long ones since the former fits the definition of *minor withdrawal behavior* as they are subtle while the latter are more overt.

Job Demands-Resources Model and Withdrawal

Two of the concepts that were found to affect withdrawal behaviors are job-demands and job-resources. According to the Job Demands-Resources model (JD-R; Bakker & Demerouti, 2007; Demerouti, Bakker, De Jonge, Janssen, & Schaufeli, 2001; Demerouti, Bakker, Nachreiner, & Schaufeli, 2001), Job demands are "...those aspects of the job that require sustained physical and/or psychological effort or skills, and therefore have certain physiological and/or psychological costs". Examples of job demands are high workload, time pressure, and role ambiguity. Job resources are "…those aspects of the job that are functional in achieving work goals, reduce job demands and the associated costs, or stimulate personal growth, learning and development" (Bakker & Demerouti, 2007). There is extensive support for the idea that job demands may hamper employee well-being and lead to withdrawal behaviors (Bakker, Demerouti, & Schaufeli, 2003; Bakker, Demerouti, de Boer, & Schaufeli, 2003; Demerouti, Bakker, Nachreiner, & Schaufeli, 2000; Som, 2004), whereas job resources may stimulate a motivational process leading to job-related learning and organizational commitment (Bakker, Demerouti, & Euwema, 2005; Bakker & Demerouti, 2007; Som, 2004).

According to the JD-R model, there is a dual-process underlying the development of job strain and motivation. In the first psychological process, job demands can exhaust employees' mental and physical resources and may lead to a depletion of energy (i.e., exhaustion). When depleted, an employee might wish to withdraw from the situation generating the problem (Bakker, Demerouti, & Schaufeli, 2003; Muraven & Baumeister, 2000). In the second psychological process, job resources are suggested to have a motivational potential and to lead to engagement, whether through the satisfaction of basic needs or through the achievement of work goals (Bakker & Demerouti, 2007). The presence of job resources may foster the willingness to dedicate efforts and abilities to the work tasks.

Our study focuses on *minor withdrawal behaviors*, which are behaviors that occur during the work shift and are hard to monitor by management. These behaviors are quite subtle and are part of an employee shift, as opposed to lateness that occurs before a shift begins, or absenteeism that means that an employee did not arrive to one's shift. We assume that the antecedents of these *minor withdrawal behaviors* are specific demands of the job that are relevant to a particular moment and are short-lasting. These demands that fluctuate over time resemble a "state", as opposed to general characteristics of the job, which resemble a "trait". We will refer to these specific demands from now onwards as *work demands*. We will create an index of work demands composed of operational variables that impose demands on a <u>specific</u> employee, i.e., the number of chats handled, the number of words read and wrote, and the number of concurrent chats during a defined time interval. Hence, our first hypothesis:

H1: Work Demands increase Employee Minor Withdrawal Behaviors

In the following section we allege that customer expressed emotion can impact employee behavior. Specifically, we argue that customer expressions of negative emotion can impose a demand, while customer expressions of positive emotion can act as a resource, and hence can affect withdrawal behaviors.

Customer Emotions and Withdrawal

Customers present a rich source of work stress and work demands (Dormann & Zapf, 2004; Groth & Grandey, 2012; Wegge, Vogt, & Wecking, 2007). A customer service employee interacts with many customers per day; each customer presents unique demands and may express different emotions during the service interaction. One of the reasons that customer service interactions may induce high levels of stress among employees is that employees are practically forced by companies' policies to treat customers as if they are always right, even when they are clearly not (Grandey, Dickter, & Sin, 2003; Groth & Grandey, 2012). Interactions with customers were found to be more demanding for employees than other work interactions, such as supervisors and colleagues' interactions. When interacting with customers, employees must suppress their anger, which forces them to use more emotional control and regulation (Grandey, Rafaeli, Ravid, Wirtz, & Steiner, 2010) thus depleting employees' cognitive resources.

Service interactions may be emotionally neutral, but can also be emotionally intense since customers frequently express negative emotions such as anger and frustration. For example, a research found that customer expressions of anger towards employees are perceived as highly legitimate, whereas employees are not allowed to express anger towards customers (Ravid, Rafaeli, & Grandey, 2010). In another research, when asked to report about the frequency of hostile callers per day, call-center employees reported 10 customer aggression events, which constitute about 15-20 percent of total calls per day (Grandey, Dickter, & Sin, 2004). Various findings in the literature show that customer emotions have a fundamental effect on employee well-being. For example, in the study described above, most of the employees reported that they interact with verbally aggressive customers on a daily basis and the findings revealed that the frequency of customer aggression is related to the intensity of stress and burnout (Grandey et al., 2004). Another research has shown that unfriendly customer behaviors promoted strain and reduced employee well-being compared with friendly customer behaviors (Wegge et al., 2007).

According to the Conservation Of Resources (COR; Hobfoll, 1989) model of stress, individuals strive to retain, protect and build resources. Resources are limited and stressors in the environment can decrease their number and strength. In contrast, other factors in the environment can increase resource availability. On the basis of the principles of COR theory, an individual whose resources are hampered will try to restore them. One way a person can act to restore resources is by withdrawing from the workplace, either by staying at home, or being late for work for example (Sliter, Sliter, & Jex, 2012; Wright & Cropanzano, 1998). Customer negative interactions might act as a threat to lose resources and may lead to a need to restore resources, possibly by withdrawing from the job (Sliter et al., 2012).

Moreover, exposure to expressions of customer negative emotions were found to take a cognitive toll from employees (Rafaeli et al., 2012). Research also suggests that exposure to expressions of negative emotions is likely to deplete employees (Muraven & Baumeister, 2000), and such a depletion is likely to translate into employee burnout and withdrawal behaviors such as tardiness or absenteeism (Sliter et al., 2012).

Employees constantly monitor the goal of satisfying customers, and customer expressions of negative emotions were suggested to serve as a signal for a discrepancy from this goal (Diefendorff & Gosserand, 2003). In order to reduce this discrepancy, employees use emotion regulation strategies, a cognitively demanding process. Because the exposure to customer emotions occurs during the shift, it has an influence on employees' immediate actions (Gabriel & Diefendorff, 2015). Thus, we suggest that an exposure to an extremely angry customer will probably lead an employee to want a break after the chat is completed. Hence, our second hypothesis:

H2a: Customer Negative Emotions increase Employee Minor Withdrawal Behaviors

In contrast, according to the Emotions as Social Information theory (EASI; Van Kleef, De Dreu, & Manstead, 2010), individuals use their partner's emotions to make sense of a situation and as inputs to their social decisions. When observing anger of a partner in an interaction, one might infer that the partner's goals are being frustrated and receive a signal of blame. On the other hand, happiness is a signal of goal achievement, and therefore of a favorable environment. In a similar way, expressions of negative emotions by customers may signal that something in the situation is unfavorable and needs a change. Building on the EASI theory, we suggest that customer negative emotions can work as a motivator and urge the employee to work harder in order to meet customer demands. Hence, we present a competing hypothesis:

H2b: Customer Negative Emotions decrease Employee Minor Withdrawal Behaviors

In a similar way to negative emotions, customer positive emotions can also have dysfunctional outcomes. For example, a study found that happiness can lead to loafing and procrastination (Parrott, 2001). In accordance with the EASI theory (Van Kleef et al., 2010), the exposure to customer positive emotions may lead the employee to believe that the situation is safe and free from problems, thus generating thoughts that one can relax and take a break. Moreover, the positive situation can be perceived as a success, leading employees to reward themselves by taking more frequent or longer breaks. Hence, we hypothesize that:

H3a: Customer Positive Emotions increase Employee Minor Withdrawal Behaviors

Customer service interactions may represent opportunities to both gain and lose resources (Dormann & Zapf, 2004). A competing analysis may view customer positive emotions as a source of resources for employees. This analysis would therefore suggest that employees are strengthened by customer positive emotions and therefore less likely to withdraw afterwards. Customer positive interactions can be seen as a success, meaning that it might act to restore resources for the employee. It was suggested that positive emotions create an accumulation of personal resources, which, in a similar way to job-resources, can moderate the effect of job-demands on work engagement and job performance (Bakker & Demerouti, 2008). Moreover, positive emotions were found to increase future positive emotions, meaning to create more personal resources (Fredrickson & Joiner, 2002). Hence, we hypothesize that:

H3b: Customer Positive Emotions decrease Employee Minor Withdrawal Behaviors

Customer Emotions as Moderators of the Depleting Effects of Work Demands

The JD-R model postulates that job resources may buffer the effect of job demands on strain (Bakker & Demerouti, 2007), meaning that the relationship between job demands and strain is weaker in the presence of high job resources. Moreover, the JD-R model proposes that job resources are particularly influential when job demands are high. For example, research has shown that job resources, such as autonomy and social support from colleagues, buffered the effect of work overload on exhaustion (Bakker, Demerouti, & Euwema, 2005). In a study of teachers, job resources, such as supervisor support, influenced teachers' work engagement especially when pupil misbehavior was an important job demand (Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007). Another example is a study of dentists, which found that job resources such as positive patient contacts were able to diminish the negative effect of qualitative workload, as measured in self-report items, on work engagement (Hakanen, Bakker, & Demerouti, 2005).

According to the JD-R model and following our previous hypotheses, we suggest that customer negative emotions can act as additional job demands, whereas customer positive emotions can act as job resources. Drawing on this, we propose that customer negative emotions amplify the influence of work demands on work withdrawal. In contrast, we propose that customer positive emotions diminish this influence. Hence, our final hypotheses are:

H4: Customer Emotions moderate the effect of Work Demands on Employee Minor Withdrawal Behaviors, such that:

H4a: Customer Negative Emotions strengthen the effect of Work Demands on Employee Minor Withdrawal Behaviors

H4b: Customer Positive Emotions weaken the effect of Work Demands on Employee Minor Withdrawal Behaviors

Method

Overview

The current study aims to test the hypotheses mentioned above in a new way. The current study explores natural real-life customer service interactions conducted in writing between employees and customers where an employee simultaneously interacts with multiple customers, rather than in a laboratory setting that is rather limited in its external validity. The data is comprehensive and include all information about each interaction from the moment the customers and employees entered the system until their exit. This enables us to construct objective and non-obtrusive measurements of operational variables, such as employee duration of shift and time customers wait in queue. Moreover, we can objectively measure employee behaviors, such as taking breaks and their duration. Therefore, unlike most of the research on withdrawal behaviors that is based mainly on employees' self-reports (Chi & Liang, 2013; Erdemli, 2015; Fred, Wang, & Walumbwa, 2007; Liao et al., 2008), we have a unique opportunity for exploring the effect of objectively measured work demands on objectively measured employee withdrawal behaviors in a real-life setting. For the purposes of the current study we focus on unscheduled, spontaneous short breaks (up to fifteen minutes), which we consider as a specific type of withdrawal behavior.

The current study also explores emotion in communication conducted in writing in an attempt to understand the link between emotion expressions and operational measures. We measure customer emotions via a specially tailored tool for analyzing emotions in written service communication: An automated sentiment analysis engine. This process is fully automatic, which allows for emotion detection in large amounts of text. The current study offers a better understanding of the role of emotion in interactions, because it (1) studies customer service interactions, (2) examines spontaneous, real-life interactions rather than lab studies, (3) relies on non-obtrusive, objective measurements rather than on self-reports, and (4) examines cumulative effects (across customers) of exposure to expressions of emotions by others.

Data

Our research analyzes customer service data that were provided by LivePerson Inc. (http://www.liveperson.com/). LivePerson Inc. is a worldwide leading company in the development of Internet chat service platforms. More than 18,000 companies use LivePerson platforms, which results in more than 20 million chats per month, throughout the world. This firm provided us with real-life data, which were fully anonymized prior to analyses to ensure no violation of privacy. Thus, any identifying information, including content of messages, was removed.

Our study is based on one-month customer service data from an airline company and includes 20,355 chats, composed of 241,428 messages of customers and employees. Each message is identified by its date, time, and chat ID. In addition, we had the number of words written in each message and the author of the message (i.e., customer, employee or system). For each employee, we had full information regarding workdays, shifts' start and end time, time and duration of breaks and number of chats handled in any given time point during the shifts.

As part of its services, LivePerson developed a tool for real-time assessment of customer emotions during customer service chat interactions based on Natural Language Processing (NLP). The tool scoring is based on word count of positive (e.g., “happy”) or negative valence (e.g., “angry”) and rules (e.g., “very” as an amplifier, “not” as a negation). For example, a customer message containing the phrase “very happy” will get a higher positive score than a message containing only the word “happy”. An evaluation of the tool is described by (Yom-Tov et al., 2016), who applied the LivePerson engine to a corpus of chat-service messages. The evaluation compared the tool scores for this corpus to a human gold standard, and the reported results show highly acceptable precision and recall values for positive emotions (0.75 and 0.19[a] respectively) and negative emotions (0.75 and 0.20 respectively). The low recall values imply that the tool underestimated the frequency of expressed emotions compared to the real world data, affording a more conservative test of our predictions. This means that any effect we might find in the data is probably an underestimation of the actual effect that exists in real-life.

Defining Minor Withdrawal Behaviors

We consider ***minor withdrawal behaviors*** as short (up to 15-minute) unscheduled breaks that employees take during the course of a work shift. An employee of the chat system who wishes to take an unscheduled break does so by changing status to “inactive”. For an employee who is amidst active chats with customers this change of status does not mean an immediate break. Rather, the change of status to “inactive” means that new chats will not be

[a] The sentiment analysis engine can be modified in order to detect more of the emotions, thus increasing the recall values. LivePerson chose not to modify it due to a trade-off between precision and recall, meaning that higher recall will result in lower precision, hence claiming that emotion is present when in fact it is absent.

assigned to the employee; an actual break will begin only after other active customer chats are completed.

Our analyses examine such breaks from two perspectives; first we examine factors predicting the likelihood that an employee will take a break; then we predict the duration of a break that an employee takes.

Defining Employee Work Demands

Our database contains several indicators that can be considered as ***work demands*** measurements. Those include: the number of words each employee read and wrote, the number of chats handled and the average number of concurrent chats in a specific time interval. These indicators are correlated and expected to have similar effects on the dependent variable, so we created a "work demands" index in the following way: First, we standardized each parameter. After standardizing the four parameters, we evaluated their internal consistency. Since the Cronbach's Alphas were highly acceptable, 0.75 for predicting the likelihood that an employee will take a break and 0.84 for predicting the duration of a break, we then averaged these four parameters into one index, the *employee work demands* index.

Calculating Emotion in the Data

Defining Intensity of Emotions in a Single Message

The first step of our analysis was calculating emotion in each message. In order to do so, we used LivePerson's home-grown sentiment analysis tool for text-based emotion detection. The engine assesses intensities of emotions in a message and gives each message a numerical value. Theoretically, the value ranges from minus infinity (i.e., extremely negative emotion) to plus infinity (i.e., extremely positive emotion), which represents the intensity of emotion in it. In practice, the range of emotion scores is in [–7,7]. Values higher than zero are considered as positive emotions, and values lower than zero as negative emotions.

The following message is an example of a message that contains negative emotion, but with low intensity:

"*I am furious*"

<u>Tool coded intensity</u> – -2

<u>Modified coded intensity</u> – Positive emotion: 0, Negative emotion: 2

In contrast, the following is an example of a message with high intensity:

"*Thank you very much!!! Have a nice day!! My internet working now!!!*"

<u>Tool coded intensity</u> – +4

<u>Modified coded intensity</u> – Positive emotion: 4, Negative emotion: 0

We use messageVal(e,m,j,i) to denote the sentiment analysis engine output of the emotion intensity value for a given customer message m, of an emotional valence e handled by the employee j in a time interval i.

Defining Emotions in a Specific Time Interval

In the second step of our analysis, we calculated a value that reflects the emotional intensity of positive or negative emotions in a subset of customer messages that occurred during a relevant time interval and were handled by the same employee. The intensity of customer emotions for a given time interval was calculated as the exponential moving sum (EMS) of intensities of the messages included in it.

We use intervalVal(e,n,a,i) to denote the exponential moving sum of emotional valence e expressed by customers in the number of messages n, handled by the same employee j in a time interval i:

Equation 1. Defining Emotions in a specific time interval

$$\boldsymbol{intervalVAL(e,n,j,i) = \sum_{n}^{m=1} \alpha_e^{n-m}\, messageVAL_{(e,m,j,i)}} \,,$$

where α_e denotes the coefficient α for emotional valence e. The coefficients for negative emotions is 0.9 and for positive emotions is 0.8. We chose coefficients smaller than 1 in order to take into consideration all of the emotions the customers expressed, while assigning lower weights for emotions that were expressed earlier during the time interval than closer to its end, hence closer to the break[b]. In addition, we chose a larger coefficient for negative emotion, since negative emotions were found to have a greater impact than positive emotions (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001).

Control Variables

Definitions of the control variables:

Skill- 'Service' if the employee was a service representative, 'Sales' otherwise. Added to control for the topic of the chats and its potential complexity.

[b] Another possible method for computing emotions is a simple summation of positive or negative emotions (i.e., both coefficients are 1). Results of the different models with simple summations of customer emotions are presented in Appendix A.

Shift- 'Morning' if the employee's shift started before 1 PM, 'Evening' otherwise.

Hour- hour of the day (from 8 AM to 9 PM).

Day- day of the week (Sunday to Saturday).

Shift_Start- time passed since the shift started (in minutes). Added to control for breaks that were taken due to long time that passed since the beginning of the shift.

Rest_Time- time without assigned customers since the shift started (in minutes). Added to control for breaks that were taken due to little rest time during the shift.

Queue_Wait- customers' average wait time in queue, before the chat started (in minutes). Added as a proxy for the system load.

Emp_Wait- employee wait time for customers during chats (in minutes). Added to control for the amount of time the employee worked actively during the time interval.

M_Chat_Dur- average duration of a chat (in minutes). Added as a proxy for chat complexity.

M_Emo_Cust- average emotion in chat. Added to control for highly emotional chats, which may imply on chat complexity.

***P_Emo*_Cust**- proportion of customers expressing any emotion. Added to control for the amount of emotional chats out of total number of chats the employee handled.

Col_Num– Number of employee's colleagues. Added as a proxy for the system resources.

Analyses

In our sample, breaks are nested within employees, leading to a potential interdependence of the observations. In order to assess whether our data violate assumptions of independence, we calculated the intra-class correlation coefficient (ICC). Although we found that the ICCs in both of the samples are negligible and not significant (ICC=0.01,

$Z=1.07$, $p>0.05$ when predicting the likelihood an employee will take a break, and $ICC=0.02$, $Z=1.42$, $p>0.05$ when predicting the duration of a break employee takes) we proceeded to use hierarchical linear modeling (HLM) to account for the nested structure of the data in testing our hypotheses. Level 2 variable was the employee ID while level 1 included all other independent and dependent variables.

Model 1- Predicting Likelihood an Employee Will Take a Break

Model 1 Sample

For Model 1 we sample random time intervals during all employee work shifts so that we can predict the likelihood an employee will take a break during the specific time interval. We did not want to choose an arbitrary length for the time intervals, thus we decided to sample 12-minute intervals, as it is the average duration of a chat in our data. Within each sampled time interval we defined that an employee took a break (coded as 1) or not (coded as 0) based on whether or not there was a changed status to "inactive" during the time interval. Since we wished to predict if a break took place or not, we needed to use only events that preceded a status change. Thus, if a break was taken, we redefined the time interval between the start time of the original interval and the time the employee changed status as "Updated Time Interval". Nevertheless, if a break was not taken, the Updated Time Interval equals the original time interval. For example, if the sampled time interval was between 9:00 AM and 9:12 AM (i.e., 12 minutes), and the employee changed status at 9:08 AM, then the Updated Time Interval is between 9:00 AM and 9:08 AM (i.e., 8 minutes, See Figure 1). However, if the employee did not change status during this time interval, the Updated Time Interval remains between 9:00 AM and 9:12 AM.

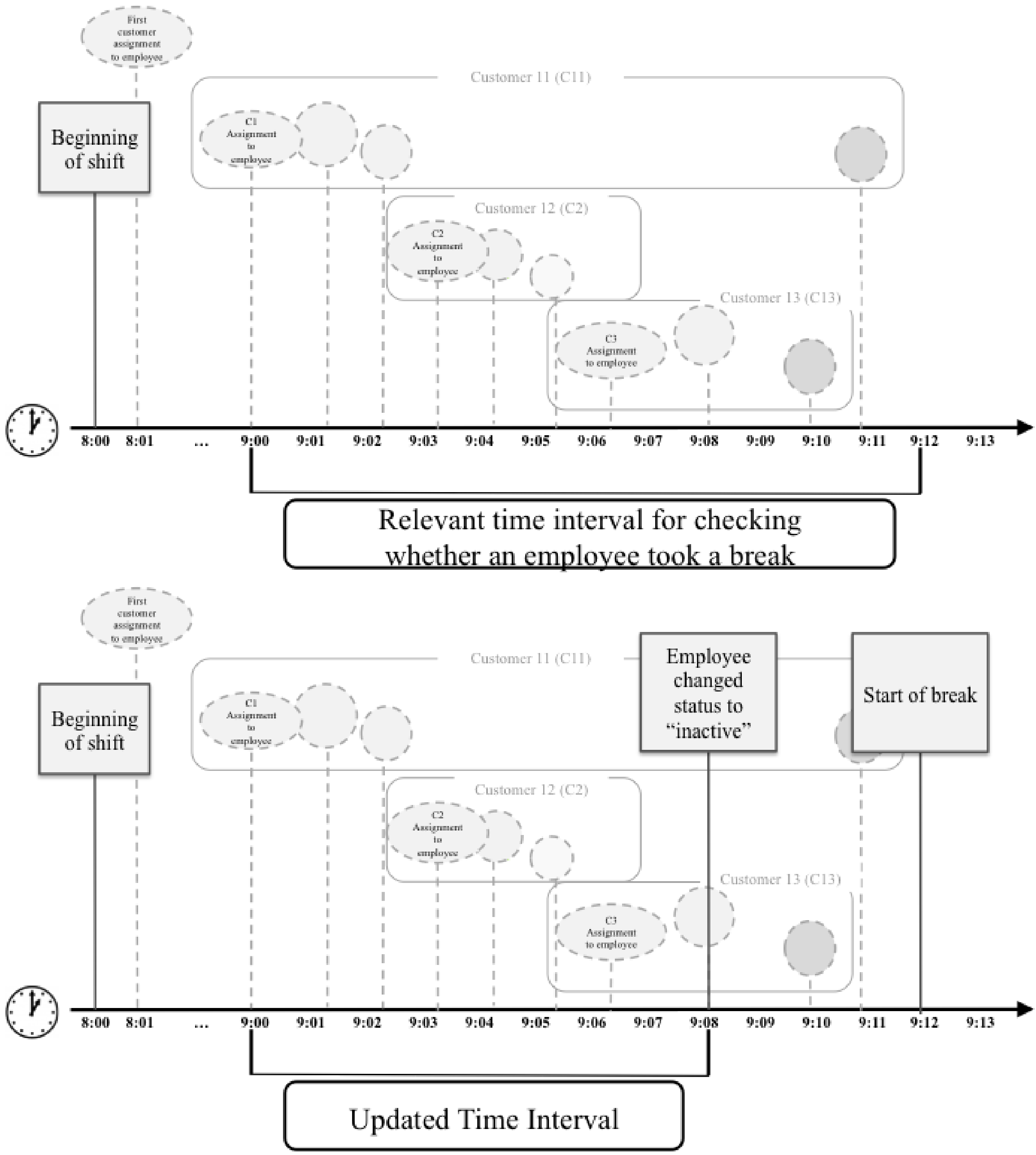

Figure 1. Illustration of 12-minute interval- Model 1- Predicting likelihood an employee will take a break

All of the variables in Model 1 are connected to events that occurred during the Updated Time Interval. Some variables are time-based, meaning that their values are correlated with the duration of the time interval. For example, the number of chats an employee handled depends on the duration of the Updated Time Interval, since an employee can handle a larger number of chats in a longer time interval. In order to correct for the different time intervals (due to the modification of the time interval if there was a status change), we divided the time-based variables by the duration of the time interval, meaning that we modified the measurements to be values per minute (e.g., number of chats an employee handled in the time interval was modified to number of chats an employee handled per minute). Variables that are not time-based were not modified (e.g., customer average wait time in queue does not depend on the duration of the time interval and hence was not modified). For a full list of the variables used in this part of the study and their operational definitions, see Table 1.

We removed outliers (+/- 2.5 SD's in work demands and in duration of the Updated Time Interval). The Model 1 sample comprises 3,084 observations (32 workdays including weekends; 40 employees, 61% sales and 39% service; 30% evening shifts that started after 1 PM).

Model 1 Results

Table 2 details the means, standard deviations and correlations of the continuous variables at level 1. Table 3 presents the means, standard deviations and correlations of the continuous variables after standardizing them and creating the work-demands index.

The model we propose for checking our hypotheses is the following:

Equation 2. Model 1

$$\log(TakeaBreak)_{i,j} = \gamma_{0,j} + \gamma_1 Control_{i,j} + \gamma_2 EmployeeWorkDemands_{i,j} + \gamma_3 CustomerNegativeEmotions_{i,j} + \gamma_4 CustomerPositiveEmotions_{i,j} + \gamma_5 CustomerNegativeEmotions_{i,j} \cdot EmployeeWorkDemands_{i,j} + \gamma_6 CustomerPositiveEmotions_{i.j} \cdot EmployeeWorkDemands_{i,j},$$

where $\log(TakeaBreak)_{i,j}$ is the likelihood that employee j will take a break in a specific time interval i and γ_{0j} is the random intercept for each employee j.

A binomial logistic regression was performed to ascertain the effects of work demands, customer positive emotions and customer negative emotions on the likelihood that an employee took a break (coded as 1, employee did not take a break coded as 0) and the results are presented in Table 4. The logistic regression model was statistically significant ($\chi^2(34) = 110.3$, $p < 0.001$). The model explained 15% (Nagelkerke R^2) of the variance in taking breaks and correctly classified 92% of cases (See Figure 2 for ROC curve). In support of Hypothesis 1, the effect of employee work demands is positive and highly significant (γ=0.96, SE=0.31, p<0.01) indicating that for every increase in one unit of work demands, the odds of an employee to take a break increase by a factor of 2.61. Although customer negative emotions is not a significant predictor (γ=0.12, SE=0.22, p>0.05) and thus Hypothesis 2 is not supported, the effect of customer positive emotions is significant (γ=0.92, SE=0.32, p<0.01), indicating that for every increase in one unit of customer positive emotions, the odds of an employee to take a break increase by a factor of 2.50. This finding is in line with Hypothesis 3a. Customer negative emotions and customer positive emotions do not act as moderators on the relationship between work demands and likelihood of an employee taking a break (γ=-0.27, SE=0.40, p>0.05 and γ=-0.13, SE=0.52, p>0.05, respectively), thus our fourth hypothesis was not supported.

Table 1. Model 1- Predicting the likelihood an employee will take a break- variables list

Variable- short name	Variable- long name	Operational definition
Continuous variables		
N_Read	Number of words read per minute	Number of words an employee read divided by the updated time interval length
N_Wrote	Number of words wrote per minute	Number of words an employee wrote divided by the updated time interval length
N_Chats	Number of chats handled per minute	Number of chats an employee handled divided by the updated time interval length
M_Concurrent	Average number of concurrent chats per minute	Average number of concurrent chats an employee handled divided by the updated time interval length
Work_Demands	Employee work demands per minute	Work demands index* computed for the employee divided by the updated time interval length
Cus_Neg_Emo	Customer negative emotions per minute	EMS** of customer negative emotions divided by the updated time interval length
Cus_Pos_Emo	Customer positive emotions per minute	EMS** of customer positive emotions divided by the updated time interval length
Shift_Start	Shift start	Time passed since the shift started (in minutes), defined as the time between the employee's shift start time and the end of the updated time interval
Rest_Time	Rest time	Time without assigned customers since the shift started (in minutes), defined as the total amount of time that the employee was on a break between the shift start time and the end of the updated time interval
Queue_Wait	Queue wait	Customers' average wait time in queue, before the chat started (in minutes), defined as the average time the employee's customers waited in queue, across all chats
Emp_Wait	Employee wait per minute	Employee wait time for customers during chats per minute (in minutes), defined as the amount of time the employee did not write to any of the concurrent customers during the time interval, divided by the updated time interval length
M_Chat_Dur	Average chat duration	Average duration of a chat (in minutes), defined as the average duration of a chat across all chats
M_Emo_Cust	Average emotion in chat	Grand mean of emotions in chat, across all chats
P_Emo_Cust	Proportion of emotional chats	Proportion of customers expressing any emotion, defined as the number of chats with any expression of emotions divided by the total number of chats
Col_Num	Number of colleagues	Number of employee's colleagues during the updated time interval
Categorical variables		
Skill	Skill	'Service' (=0) if the employee was a service representative, 'Sales' (=1) otherwise
Shift	Shift	'Morning'(=0) if the employee's shift started before 1 PM, 'Evening' (=1) otherwise
Hour	Hour of day	Hour of the day (from 8 AM to 9 PM)
Day	Day of week	Day of the week (Sunday to Saturday)
Dependent variable		
Break_Binary	Whether an employee took a break	'No' (=0) if an employee did not change status, 'Yes' (=1) otherwise

* Work demands index - average of four standardized parameters- N_read, N_wrote, N_chats and M_concurrent

** EMS = Exponential Moving Sum, based on equation 1 in the text

Table 2. Model 1- Means, standard deviations and correlations- Raw variables

Variable		Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Shift_Start	220.2	157.9													
2	Rest_Time	16.16	34.01	.38**												
3	Queue_Wait	0.85	1.39	.04*	.19**											
4	M_Chat_Dur	8.33	5.59	0.03	0.01	.12**										
5	Emp_Wait	0.28	0.14	0	0.02	-.06**	.04*									
6	P_Emo_Cust	0.47	0.3	-.06**	0	.06**	.14**	.06**								
7	M_Emo_Cust	0.12	0.31	0	-.04*	-.07**	-0.01	-0.02	.27**							
8	Col_Num	4.81	1.89	-0.02	0	-.08**	-.04*	.06**	-0.02	-.04*						
9	Cus_Neg_Emo	0.05	0.1	0.01	.05**	.05**	0.03	-.04*	.24**	-.37**	-.04*					
10	Cus_Pos_Emo	0.08	0.21	0.02	-0.01	-0.03	-0.01	-0.02	.23**	.40**	-.08**	-.04*				
11	N_Chats	0.39	0.39	.10**	0.02	-.06**	-.15**	-.11**	-.12**	0.02	-.17**	.24**	.45**			
12	N_Wrote	30.45	17.62	-0.02	-0.02	-.07**	-.07**	-.04*	.05**	0.01	-.11**	.20**	.10**	.33**		
13	N_Read	15.09	11.44	-0.01	0	-.04*	-.05**	-0.01	.09**	-.04*	-.13**	.26**	.09**	.43**	.39**	
14	M_Concurrent	0.27	0.6	.10**	0.03	0.01	0.02	-.12**	-.09**	0	-.14**	.18**	.24**	.81**	.15**	.42**

Note . * p < .05. ** p < .01.

Table 3. Model 1- Means, standard deviations and correlations- Scaled variables

Variable	Mean	*SD*	1	2	3	4	5	6	7	8	9	10
1 Shift_Start	-0.03	0.99										
2 Rest_Time	-0.02	0.96	.38**									
3 Queue_Wait	0	0.99	.04*	.19**								
4 M_Chat_Dur	0	0.99	0.02	0.01	.12**							
5 Emp_Wait	0.01	0.97	0.02	0.03	-.06**	.05**						
6 P_Emo_Cust	0.03	0.98	-.04*	0.01	.07**	.15**	.05**					
7 M_Emo_Cust	0	0.97	0.01	-.04*	-.07**	-0.01	-0.01	.27**				
8 Col_Num	4.85	1.88	0	0	-.09**	-.05**	.04*	-0.03	-0.3			
9 Cus_Neg_Emo	-0.03	0.65	-0.03	.04*	.08**	.04*	0	.35**	-0.46**	-0.03		
10 Cus_Pos_Emo	-0.04	0.4	0	0	-0.03	0.03	0.02	.47**	0.60**	-.03	-.07**	
11 Work_Demands	-0.05	0.39	-.05**	-0.02	-.08**	-.17**	0.02	.09**	-.02	-.15**	.19**	.15**

Note . * p < .05. ** p < .01.

Table 4. Model 1- Hierarchical Linear Modeling (HLM) results

	Null model			Model 1 (fixed slopes)		
	γ	*SE*	exp(γ)	γ	*SE*	exp(γ)
Level 1						
(Intercept)	-3.44***	0.13		-3.73***	0.83	0.02
Control variables						
Skill- Sales[a]				-0.03	0.32	0.97
Shift- Evening[b]				-0.48	0.49	0.62
Hour - 9 Am[c]				-0.87	1.24	0.42
Hour - 10 Am[c]				1.21	0.84	3.36
Hour - 11 Am[c]				0.03	0.96	1.03
Hour - 12 PM[c]				0.21	0.97	1.23
Hour - 1 PM[c]				0.31	0.96	1.36
Hour - 2 PM[c]				1.28	0.94	3.60
Hour - 3 PM[c]				1.78†	0.97	5.93
Hour - 4 PM[c]				0.98	1.01	2.65
Hour - 5 PM[c]				1.12	1.03	3.07
Hour - 6 PM[c]				0.85	1.07	2.34
Hour - 7 PM[c]				1.59	1.08	4.88
Hour - 8 PM[c]				1.93†	1.16	6.86
Hour - 9 PM[c]				1.61	1.23	5.00
Day - Sunday[d]				-0.79*	0.39	0.45
Day - Monday[d]				-0.05	0.34	0.95
Day - Tuesday[d]				-0.07	0.37	0.93
Day - Wednesday[d]				0.07	0.37	1.07
Day - Thursday[d]				-1.17*	0.50	0.31
Day - Saturday[d]				-0.72†	0.41	0.48
Shift_Start				0.34	0.22	1.41
Rest_Time				0.05	0.11	1.05
M_Chat_Dur				0.25**	0.09	1.28
Emp_Wait				-0.02	0.11	0.98
Queue_Wait				0.07	0.10	1.07
P_Emo_Cust				-0.25	0.15	0.78
M_Emo_Cust				-0.17	0.18	0.85
Col_Num				-0.09	0.08	0.92
Independent variables						
Work_Demands				0.96**	0.31	2.61
Cus_Neg_Emo				0.12	0.22	1.13
Cus_Pos_Emo				0.92**	0.32	2.50
Work_Demands X Cus_Neg_Emo				-0.27	0.40	0.76
Work_Demands X Cus_Pos_Emo				-0.13	0.52	0.88
Variance components						
Intercept variance (Level 2)		0.09			0.11	
-2 Log likelihood		888.1			777.8	
AIC		892.1			849.8	

Dependent variable: Whether an employee took a break (no=0, yes=1)

(a) Compared with Service (b) Compared with Morning (c) Compared with 8AM (d) Compared with Friday

Note. † $p < .10$ * $p < .05$. ** $p < .01$. *** $p < .001$. n = 40 employees (Level 2); n = 3,084 time intervals (Level 1).

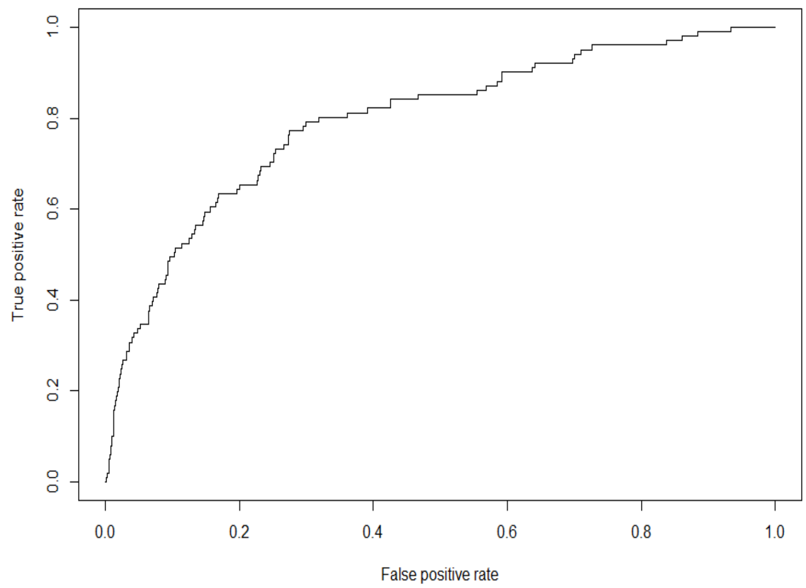

Figure 2. Model 1- ROC Curve

Model 2- Predicting Duration of Employee Break

Model 2 Sample

To test predictability of the duration of breaks we sampled 30-minute intervals prior to employee spontaneous, unscheduled breaks (i.e., unscheduled breaks of less than fifteen minutes). We chose time intervals of 30-minutes because we wanted intervals to include sufficient information from both before and after the point where employees changed status. As noted above, a change of status does not immediately start a break because active chats still need to be completed. For example, if an employee changed status at 11:27 AM but the break started at 11:35 AM, the relevant time interval is between 11:05 AM and 11:35 AM (See Figure 3).

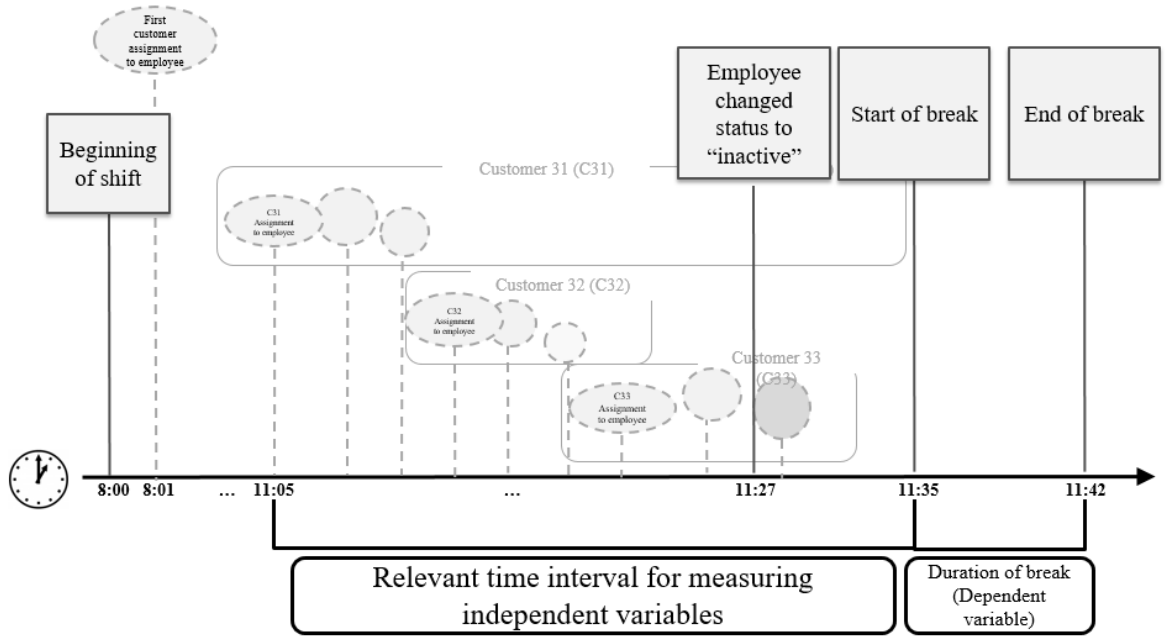

Figure 3. Illustration of 30-minute interval. Model 2- Predicting duration of employee break.

As in part one, we removed outliers (+/- 2.5 SD's from the mean in work demands and in duration of the break). The Model 2 sample comprises 835 observations (32 workdays including weekends; 40 employees, 61% sales and 39% service; 32% evening shifts that started after 1 PM). For a full list of the variables used in this part of the study and their operational definitions, see Table 5.

Model 2 Results

Table 6 details the means, standard deviations and correlations at level 1 of the continuous variables. Table 7 presents the means, standard deviations and correlations of the continuous variables after standardizing them and creating the work-demands index.

Table 5. Model 2- Predicting the duration of an employee's break- variables list

Variable- short name	Variable- long name	Operational defenition
Continuous variables		
N_Read	Number of words read	Number of words an employee read
N_Wrote	Number of words wrote	Number of words an employee wrote
N_Chats	Number of chats handled	Number of chats an employee handled
M_Concurrent	Average number of concurrent chats	Average number of concurrent chats an employee handled
Work_Demands	Employee work demands	Work demands index* computed for the employee
Cus_Neg_Emo	Customer negative emotions	EMS** of customer negative emotions
Cus_Pos_Emo	Customer positive emotions	EMS** of customer positive emotions
Shift_Start	Shift start	Time passed since the shift started (in minutes), defined as the time between the employee's shift start time and the end of the updated time interval
Rest_Time	Rest time	Time without assigned customer since the shift started (in minutes), defined as the total amount of time that the employee was on a break between the shift start time and the end of the updated time interval
Queue_Wait	Queue wait	Customers' average wait time in queue, before the chat started (in minutes), defined as the average time the employee's customers waited in queue, across all chats
Emp_Wait	Employee wait	Employee wait time for customers during chats (in minutes), defined as the amount of time the employee did not write to any of the concurrent customers during the time interval
M_Chat_Dur	Average chat duration	Average duration of a chat (in minutes), defined as the average duration of a chat across all chats
M_Emo_Cust	Average emotion in chat	Grand mean of emotions in chat, across all chats
P_Emo_Cust	Proportion of emotional chats	Proportion of customers expressing any emotion, defined as the number of chats with any expression of emotions divided by the total number of chats
Col_Num	Number of colleagues	Number of employee's colleagues during the time interval
Categorical variables		
Skill	Skill	'Service' (=0) if the employee was a service representative, 'Sales' (=1) otherwise
Shift	Shift	'Morning'(=0) if the employee's shift started before 1 PM, 'Evening' (=1) otherwise
Hour	Hour of day	Hour of the day (from 8 AM to 9 PM)
Day	Day of week	Day of the week (Sunday to Saturday)
Dependent variable		
Break_Dur	Duration of an employee's break	The duration of an employee's break (in seconds), defined as the time between the employee finished active chats after switching to "inactive" and status change back to "active"

* Work demands index - average of four standardized parameters- N_read, N_wrote, N_chats and M_concurrent

** EMS = Exponential Moving Sum, based on equation 1 in the text

Table 6. Model 2- Means, standard deviations and correlations- Raw variables

Variable		Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Shift_Start	331.2	169.2														
2	Rest_Time	27.5	43.38	.31**													
3	Queue_Wait	0.98	2.05	0.03	.23**												
4	M_Chat_Dur	10.73	4.38	.09*	0.02	.22**											
5	Emp_Wait	8.11	3.31	0.06	-.09**	-.12**	.14**										
6	P_Emo_Cust	0.57	0.27	-0.02	0.02	0.02	.21**	.07*									
7	M_Emo_Cust	0.14	0.26	-0.04	-0.05	-0.05	-0.06	-0.02	.26**								
8	Col_Num	5.5	2.09	-0.01	.08*	-0.02	-0.02	-0.05	-0.01	-.10**							
9	Cus_Neg_Emo	0.62	0.8	0.03	0.02	0	0.07	.07*	.23**	-.37**	0.06						
10	Cus_Pos_Emo	1.23	1.2	0.01	-0.02	-0.04	0.02	0.05	.33**	.46**	-0.07	-0.06					
11	N_Chats	4.92	2.22	0.02	-.07*	-.16**	-.38**	.28**	-.13**	-0.02	-0.06	.09**	0.05				
12	N_Wrote	720.5	361	-0.06	-.10**	-.14**	-0.01	.28**	0.05	0.02	-.07*	.14**	.11**	.68**			
13	N_Read	329.9	170.6	-0.04	-0.04	-.12**	0	.34**	.12**	0.02	-.10**	.22**	.17**	.64**	.77**		
14	M_Concurrent	1.93	0.67	.08*	.10**	.12**	.19**	.22**	.09**	-.07*	-0.05	.14**	.07*	.46**	.42**	.41**	
15	Break_Dur	310.6	289.3	-.10**	-.11**	0	0.03	.09**	0.01	0.03	-0.01	0	0.06	.08*	.12**	.10**	.11**

Note . * p < .05. ** p < .01.

Table 7. Model 2- Means, standard deviations and correlations- Scaled variables

Variable		M	*SD*	1	2	3	4	5	6	7	8	9	10	11
1	Shift_Start	0	1											
2	Rest_Time	0.01	1	.31**										
3	Queue_Wait	0	1.01	0.03	.23**									
4	M_Chat_Dur	0	1	.08*	0.03	.22**								
5	Emp_Wait	0	1.01	0.06	-.09**	-.12**	.14**							
6	P_Emo_Cust	0	1	-0.02	0.03	0.02	.21**	.08*						
7	M_Emo_Cust	0	1	-0.04	-0.05	-0.06	-0.06	-0.02	.26**					
8	Col_Num	5.54	2.04	-0.01	0.06	-0.02	-0.01	-0.04	0	-.09**				
9	Cus_Neg_Emo	0	1	0.05	0.03	0	0.06	.07*	.24**	-.37**	0.06			
10	Cus_Pos_Emo	0	1	0.01	-0.02	-0.04	0.02	0.04	.33**	.46**	-0.06	-0.06		
11	Work_Demands	-0.02	0.65	-0.02	-.08*	-.16**	-.14**	.34**	0.02	0.01	-.07*	.16**	.14**	
12	Break_Dur	309.46	289.47	-.09**	-.11**	0	0.04	.09**	0.02	0.03	-0.01	0	0.06	.10**

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

The model we propose for checking our hypotheses is the following:

Equation 3. Model 2

$$\text{DurationofBreak}_{ij} = \gamma_{0j} + \gamma_1 Control_{i,j} + \gamma_2 EmployeeWorkDemands_{i.j} +$$
$$\gamma_3 CustomerNegativeEmotions_{i.j} + \gamma_4 CustomerPositiveEmotions_{i,j} +$$
$$\gamma_5 CustomerNegativeEmotions_{i.j} \cdot EmployeeWorkDemands_{i,j} +$$
$$\gamma_6 CustomerPositiveEmotions_{i,j} \cdot EmployeeWorkDemands + \varepsilon_{ij} \ ,$$

where $\text{DurationofBreak}_{i,j}$ is the duration of the break an employee j takes at the end of a specific time interval i and $\gamma_{0,j}$ is the random intercept for each employee j.

We conducted a set of analyses with duration of break as the dependent variable and the results are presented in Table 8. In order to test Hypothesis 1, we examined the main effect of work demands on duration of break and the results indicate a marginally significant positive effect (γ=27.32, SE=16.65, p<0.10). Although we did not find significant main effects of customer negative or positive emotions (γ=-7.00, SE=11.42, p>0.05, γ=16.41, SE=11.23, p>0.05, respectively), and thus our second and third hypotheses were not supported, we did find significant interactions. Our fourth hypothesis regarding the moderating role of customer emotions in the relationship between work demands and duration of break was supported. Customer negative emotions act as a positive moderator (γ=38.92. SE=17.88, p<0.05), whereas customer positive emotions act as a negative moderator (γ=-40.71, SE=16.25, p<0.05); for simple slopes graphs, see Figure 4 (We plotted both interactions at conditional values of the moderators, i.e., 2 SDs above and below the means) These findings imply that when customers express high negative emotions, higher

Table 8. Model 2- Hierarchical Linear Modeling (HLM) results

	Null model		Model 1 (fixed slopes)	
	γ	*SE*	γ	*SE*
Level 1				
(Intercept)	304.99**	12.68	246.93**	93.27
Control variables				
Skill- Sales[a]			4.76	30.31
Shift- Evening[b]			33.10	44.05
Hour - 9 Am[c]			52.07	92.83
Hour - 10 Am[c]			161.66†	90.76
Hour - 11 Am[c]			32.46	92.62
Hour - 12 PM[c]			-26.86	94.65
Hour - 1 PM[c]			38.20	92.85
Hour - 2 PM[c]			181.09†	98.04
Hour - 3 PM[c]			78.85	102.40
Hour - 4 PM[c]			-9.02	102.24
Hour - 5 PM[c]			34.21	103.67
Hour - 6 PM[c]			187.89†	104.75
Hour - 7 PM[c]			46.51	108.30
Hour - 8 PM[c]			167.87	111.83
Hour - 9 PM[c]			18.37	118.18
Day - Sunday[d]			-2.24	35.46
Day - Monday[d]			40.11	32.26
Day - Tuesday[d]			6.27	34.83
Day - Wednesday[d]			20.54	35.76
Day - Thursday[d]			16.44	38.17
Day - Saturday[d]			-34.45	36.86
Shift_Start			-11.70	20.76
Rest_Time			-31.06*	13.15
Queue_Wait			7.40	10.23
M_Chat_Dur			11.38	10.42
Emp_Wait			19.5†	10.44
P_Emo_Cust			0.51	11.49
M_Emo_Cust			-13.32	13.15
Col_Num			-4.49	7.27
Independent variables				
Work_Demands			27.32†	16.65
Cus_Neg_Emo			-7.00	11.42
Cus_Pos_Emo			16.41	11.23
Work_Demands X Cus_Neg_Emo			38.92*	17.88
Work_Demands X Cus_Pos_Emo			-40.71*	16.25
Variance components				
Within-group variance (Level 1)	81,994		69,528	
Intercept variance (Level 2)	1,696		1,559	
-2 Log likelihood	11,830		11,694	
Pseudo-R square	0.15			

Dependent variable: duration of break

(a) Compared with Service (b) Compared with Morning (c) Compared with 8AM (d) Compared with Friday

Note. †p< .10. * p < .05. ** p < .01. *** p < .001. n = 40 employees (Level 2); n = 835 time intervals (Level 1).

Pseudo- R square values at each level were computed using the formula recommended by Snijders and Bosker (2012).

work demands lead to longer breaks. In contrast, when customers express high positive emotions, the effect reverses, and higher work demands lead to shorter breaks.

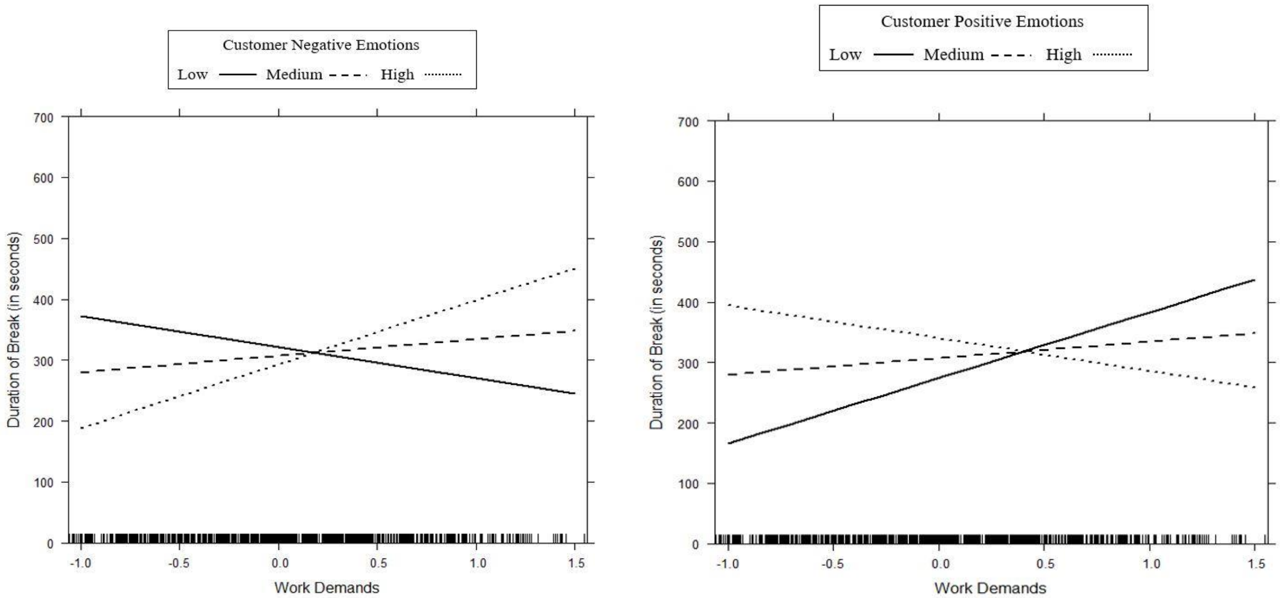

Figure 4. Model 2- Customer Emotion moderate the effect of Work Demands on the duration of break

Discussion

The current study presents the use of automated sentiment analysis to detect emotionally-charged messages in large-scale data of chat-based customer-service interactions. The study also uses objective measurements of operational variables as an index of work demands, in contrast to previous work on work demands, which was based on self-reports, which suffer from various limitations (Donaldson & Grant-Vallone, 2002; Grøvle et al., 2012; Johns & Miraglia, 2015; Paulhus & Vazire, 2007).

The results of our analyses revealed that customer positive emotions and employee work demands increase the likelihood that employee will withdraw from the work. Although the effect of work demands is reasonable, the effect of customer positive emotions might seem counterintuitive. One of the explanations for this effect can be the interpretation of the emotions the customer presents. Employees can interpret customer expression of positive emotions as a signal for a favorable situation, leading to an increase in employees self-esteem (Brett & Drasgow, 2002; Wang, Liao, Zhan, & Shi, 2011), which enables them to enjoy a "prize" in the form of a break. Thus, we suggest that employees allow themselves to take more breaks when there is no reason to believe that something is wrong (i.e., when it appears that customers are satisfied).

In addition, we found that customer negative emotions strengthen the positive effect of employee work demands on the duration of the withdrawal behaviors of the employee. In contrast to customer negative emotions, customer positive emotions reverse the effect of employee work demands on the duration of the withdrawal behaviors, meaning that in the presence of high work demands, customer positive emotions will lead to shorter withdrawal behaviors. This moderating role of customer positive emotion may suggest that this type of emotion may act as a resource, which can be used by employees when confronted with high work demands. Moreover, customer positive emotions can be rewarding, leading employees to avoid long breaks in order to continue interacting with customers, a behavior that led to rewards in the past. Although the negative effect of customer positive emotion on the duration of the break seems to contradict its positive effect on the likelihood of a break, it does not have to be the case. It can be that customer positive emotion leads to more breaks, yet shorter ones.

Untangling the Effects of Customer Emotions on Service Employees

At first glance, it might seem surprising that customer negative emotions do not lead to more frequent or longer withdrawal behaviors by themselves. As we proposed in the introduction, there are two competing forces, namely customer negative emotions as an additional work demand that will increase the need for additional or longer breaks, versus customer negative emotions as a motivator for changing the unpleasant situation and thus staying in the situation and acting to improve it rather than avoiding it in the form of a break. It may be that these competing forces offset each other thus resulting in the non-significant effect we found. In addition, it is possible that employees in customer-service jobs perceive expressions of negative emotions by customers as an inherent part of their job; hence, the presence of customer negative emotions matches their expectations. If employees perceive customer negative emotions as a “normal” part of their job, it may be less stressful and may not lead to withdrawal behaviors (Grandey, Dickter, & Sin, 2003).

It seems that both customer positive and negative emotions obtain their significance in the presence of high work demands. Customer negative emotions will lead to longer withdrawal behaviors only if work demands are high, whereas customer positive emotions will lead to shorter breaks only in the presence of high work demands. We offer that under high work demands, customer negative emotions can act as an additional work demand, while customer positive emotions can act as a work resource.

Implications

Our findings offer strong empirical support for the Job Demands-Resources model (JD-R; Bakker & Demerouti, 2007). With the use of real-time non-obtrusive operational measures, we showed that work demands do increase withdrawal behaviors. Moreover, using an automated sentiment analysis tool, which was developed specifically for chat-based customer service, we showed the importance of customer emotions in predicting withdrawal behaviors.

The findings of the current study highlight the importance of attention to work demands and to customer emotions, as it seems that employees may use withdrawal behaviors as a coping mechanism when work demands and customer negative emotions are high. Managers should attend to work demands that employees experience in order to decide on the ideal number of employees to staff. In addition, given that the sentiment analysis tool used in the current study can detect emotionally-charged messages in real-time, managers can decide on routing of incoming customers according to the exposure of employees to customer positive and negative emotions. Optimally, the system itself will monitor in real-time the work demands employees experience and the customer emotions they are exposed to, and will direct incoming customers to employees that have lower work demands, are exposed to low customer negative emotions or to high customer positive emotions at the particular moment.

Limitations and Future Research

A possible limitation of the current study is that the recall rates of the sentiment analysis tool we have used are somewhat low (0.19-0.20). These numbers suggest that the tool does not recognize all of the emotions that exist in the data. A recall of 0.20 for example means that the tool only identifies 20 percent of emotionally-charged messages as containing emotions. Although we probably miss some of the customer emotions, these numbers may imply that our test is quite conservative and that the effects we witness are stronger in reality.

Another limitation is that we did not have access to the demographic details of customers and employees or to the content of the messages. It may be possible that regardless of the emotions the customers expressed, one of the demographics of the employees or the content of specific interactions (e.g., a complicated complaint) was the cause of longer or shorter withdrawal behaviors. Even though we controlled for the average length of an interaction, we cannot rule out this alternative explanation and future research is needed.

Further research using the sentiment analysis tool we used might also shed light on the costs or benefits of these withdrawal behaviors. Future research can explore whether these behaviors have a positive influence on different outcomes, such as superior performance of the employee (e.g., shorter response time) and higher customer positive emotions. It may be that employees use these withdrawal behaviors in order to gain back resources, a strategy that might improve their performance afterwards (Westman & Eden, 1997). On the other hand, it may be that these behaviors are just a temporary relief and that employees will keep on behaving in similar ways, which allow them to avoid aversive situations (Darr & Johns, 2008).

At last, a potential mediator that we wish to explore is employee emotions. The sentiment analysis tool we used is not yet adjusted for employee emotions so we cannot measure them. We suggest that the effects of work demands and customer emotions on withdrawal behaviors might work through their influence on employee emotions. For instance, it may be that high work demands, combined with high customer negative emotions, lead to high employee negative emotions, which in turn will lead to more frequent or longer withdrawal behaviors. We hope that as part of the ongoing development of the tool, it will be adjusted for employee emotions also, allowing for more profound analyses of the effects of emotions in chat-based customer service.

Conclusions

The current work highlights the importance of attention to work demands and to customer emotions and offers both theoretical and practical implications for the design of chat platforms, including staffing of employees and routing of customers. Although future research is needed, the findings offer evidence of the influence of work demands and customer emotions on employee withdrawal behaviors in real-life data.

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Appendix A

Table 9. Model 1- Hierarchical Linear Modeling (HLM) results, with simple summation of customer emotion

	Null model			Model 1 (fixed slopes)		
	γ	*SE*	exp(γ)	γ	*SE*	exp(γ)
Level 1						
(Intercept)	-3.44***	0.13		-3.68***	0.83	0.03
Control variables						
Skill- Sales[a]				-0.10	0.32	0.90
Shift- Evening[b]				-0.53	0.49	0.59
Hour - 9 Am[c]				-0.84	1.24	0.43
Hour - 10 Am[c]				1.27	0.84	3.55
Hour - 11 Am[c]				0.09	0.96	1.09
Hour - 12 PM[c]				0.24	0.97	1.27
Hour - 1 PM[c]				0.40	0.96	1.50
Hour - 2 PM[c]				1.33	0.94	3.79
Hour - 3 PM[c]				1.90*	0.96	6.69
Hour - 4 PM[c]				1.07	1.01	2.92
Hour - 5 PM[c]				1.20	1.02	3.33
Hour - 6 PM[c]				0.86	1.07	2.37
Hour - 7 PM[c]				1.66	1.08	5.25
Hour - 8 PM[c]				2.04†	1.16	7.69
Hour - 9 PM[c]				1.70	1.22	5.46
Day - Sunday[d]				-0.83*	0.39	0.44
Day - Monday[d]				-0.09	0.34	0.91
Day - Tuesday[d]				-0.11	0.37	0.89
Day - Wednesday[d]				0.05	0.37	1.06
Day - Thursday[d]				-1.19*	0.50	0.30
Day - Saturday[d]				-0.70†	0.41	0.50
Shift_Start				0.34	0.22	1.40
Rest_Time				0.04	0.12	1.04
M_Chat_Dur				0.26**	0.09	1.30
Emp_Wait				-0.04	0.12	0.96
Queue_Wait				0.06	0.10	1.06
P_Emo_Cust				-0.01	0.15	0.99
M_Emo_Cust				-0.14	0.20	0.87
Col_Num				-0.09	0.08	0.91
Independent variables						
Work_Demands				1.07**	0.33	2.92
Cus_Neg_Emo				-0.18	0.23	0.83
Cus_Pos_Emo				0.14	0.26	2.50
Work_Demands X Cus_Neg_Emo				-0.49	0.43	0.61
Work_Demands X Cus_Pos_Emo				-0.01	0.33	0.99
Variance components						
Intercept variance (Level 2)		0.09			0.11	
-2 Log likelihood		888.1			783.5	
AIC		892.1			855.5	

Dependent variable: Whether an employee took a break (no=0, yes=1)

(a) Compared with Service (b) Compared with Morning (c) Compared with 8AM (d) Compared with Friday

Note. † p <.10 * p < .05. ** p < .01. *** p < .001. n = 40 employees (Level 2); n = 3,084 time intervals (Level 1).

Table 10. Model 2- Hierarchical Linear Modeling (HLM) results, with simple summation of customer emotion

	Null model		Model 1 (fixed slopes)	
	γ	*SE*	γ	*SE*
Level 1				
(Intercept)	304.99**	12.68	227.37*	93.922
Control variables				
Skill- Sales[a]			5.017	30.512
Shift- Evening[b]			26.162	44.191
Hour - 9 Am[c]			58.412	93.057
Hour - 10 Am[c]			170.72†	91.103
Hour - 11 Am[c]			49.466	92.9
Hour - 12 PM[c]			-27.9	95.113
Hour - 1 PM[c]			56.843	93.023
Hour - 2 PM[c]			197.91*	98.259
Hour - 3 PM[c]			95.419	102.434
Hour - 4 PM[c]			12.964	102.516
Hour - 5 PM[c]			56.683	104.035
Hour - 6 PM[c]			207.68*	105.214
Hour - 7 PM[c]			66.233	108.724
Hour - 8 PM[c]			189.87†	112.113
Hour - 9 PM[c]			40.979	118.59
Day - Sunday[d]			-4.321	35.781
Day - Monday[d]			42.715	32.395
Day - Tuesday[d]			5.767	35.021
Day - Wednesday[d]			18.399	35.931
Day - Thursday[d]			17.48	38.393
Day - Saturday[d]			-30.853	37.01
Shift_Start			-13.48	20.86
Rest_Time			-30.44	13.198
Queue_Wait			5.913	10.323
M_Chat_Dur			11.939	10.486
Emp_Wait			21.83*	10.692
P_Emo_Cust			3.767	11.822
M_Emo_Cust			1.332	13.707
Col_Num			-4.564	7.224
Independent variables				
Work_Demands			32.044	21.15
Cus_Neg_Emo			-12.347	13.868
Cus_Pos_Emo			3.714	16.466
Work_Demands X Cus_Neg_Emo			34.41†	18.033
Work_Demands X Cus_Pos_Emo			-13.031	18.164
Variance components				
Within-group variance (Level 1)	81,994		70,148	
Intercept variance (Level 2)	1,696		1,597	
-2 Log likelihood	11,830		11,701	
Pseudo-R square	0.14			

Dependent variable: duration of break

(a) Compared with Service (b) Compared with Morning (c) Compared with 8AM (d) Compared with Friday

Note. †p< .10. * p < .05. ** p < .01. *** p < .001. n = 40 employees (Level 2); n = 835 time intervals (Level 1).

Pseudo- R square values at each level were computed using the formula recommended by Snijders and Bosker (2012).

השפעה של רגש לקוחות ודרישות עבודה על הפסקות לא מתוכננות של עובדי שירות:

בחינה של שירות לקוחות מבוסס צ׳אט

חיבור על מחקר

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

שלי אשתר

הוגש לסנט הטכניון - מכון טכנולוגי לישראל

חשוון, תשע"ז אוקטובר 2016

המחקר נעשה בהנחייתן של פרופ' ענת רפאלי וד"ר גלית יום-טוב בפקולטה להנדסת תעשייה וניהול

אני מודה לטכניון על התמיכה הכספית הנדיבה בהשתלמותי.

תקציר

התנהגויות נסיגה של עובדים הינן התנהגויות שעובדים מבצעים על מנת להימנע מאספקטים מסויימים של עבודתם או לצמצם את משך הזמן שהם עובדים על משימות ספציפיות, תוך כדי שמירה על חברותם בארגון, כגון העדרויות. ביטוי חמור יותר של התנהגויות נסיגה הן התנהגויות שעובדים מבצעים ומטרתן להפסיק לחלוטין את השתייכותם לארגון, כגון התפטרות. אחד הביטויים של התנהגויות נסיגה שלא נחקר באופן מספק הוא התנהגויות נסיגה מינוריות. התנהגויות אלו הן התנהגויות שמבוצעות על ידי עובדים במהלך יום העבודה ויכולות להיחשב כהתנהגויות נסיגה, על אף שלמראית עין, העובדים פועלים במסגרת המקובלת של תפקידם (מגיעים לעבודה בזמן והולכים בשעה מקובלת). כחלק מהתנהגויות אלה, העובדים לא משתמשים במשאביהם בצורה ראויה. למשל, עובדים יכולים "לחלום בהקיץ", לגלוש באינטרנט שלא למטרות עבודתם וכדומה. על אף שהתנהגויות אלו עלולות להיתפס לא משמעותיות, הן משמשות כתמרורי אזהרה להיווצרותן של התנהגויות נסיגה חמורות יותר ובעלות השלכות כלכליות משמעותיות לארגון ולכן מחייבות תשומת לב של ההנהלה.

המחקר הנוכחי בוחן את ההשפעה של רגשות של לקוחות ודרישות העבודה על התנהגויות נסיגה מינוריות של עובדי שירות, כיוון שאלה נמצאו כגורמים להתנהגויות נסיגה חמורות יותר. רוב המחקרים בנושא עד כה מסתמכים בעיקר על מדדי דיווח עצמי ממדגמים קטנים יחסית ולכן סובלים ממגבלות רלוונטיות. כמו כן, רוב המחקרים מודדים בעיקר התנהגויות נסיגה חמורות, אשר קלות יותר למדידה על ידי ההנהלה. זיהוי ומדידה של התנהגויות נסיגה מינוריות בצורה אובייקטיבית יכול לאפשר להנהלה להפנות קשב ומשאבים לטיפול בגורמים להתנהגויות אלה ובמצב אידיאלי, למנוע אותן.

במחקר הנוכחי אנו בוחנים שירות מבוסס-צ׳אט, אשר ייחודי בפוטנציאל האדיר שלו בכך שהוא מאפשר ניתוח אוטומטי של מדדים אובייקטיבים ממדגמים גדולים. אנו בוחנים בעזרת אינטראקציות שירות שנערכו דרך הפלטפורמה של חברת LivePerson Inc. (http://www.liveperson.com/) את ההשפעה של דרישות העבודה ורגשות של לקוחות (אשר מזוהים בעזרת כלי לזיהוי רגשות שפותח בחברה ומותאם לנתוני צ׳אט) על התנהגויות נסיגה מינוריות. במדגם שלנו, התנהגויות נסיגה מינוריות מוגדרות כהפסקות ספונטניות ולא מתוכננות של עובדים.

במדגם של 3,084 מרווחי זמן ו835 הפסקות שנדגמו רנדומלית מתוך חודש עבודה אחד אנו מוצאים כי: (א) דרישות עבודה גבוהות מגדילות את הסבירות שעובדים ייקחו הפסקות, (ב) דרישות עבודה גבוהות מאריכות את משכן של ההפסקות שהעובדים לוקחים, (ג) רגשות חיוביים של לקוחות מגבירים את הסבירות שעובדים ייקחו הפסקות ו(ד) רגשות חיוביים ושליליים של לקוחות ממתנים את ההשפעה של דרישות העבודה על משך ההפסקות של עובדים; כשלקוחות מבטאים רגשות שליליים בעוצמה גבוהה, דרישות עבודה גבוהות מובילות להפסקות ארוכות יותר. לעומת זאת, כשלקוחות מבטאים רגשות חיוביים בעוצמה גבוהה, ההשפעה מתהפכת ודרישות עבודה גבוהות מובילות להפסקות קצרות יותר.

ממצאים אלה מראים שלרגשות של לקוחות יש השפעה על התנהגויות נסיגה מינוריות של עובדים. רגשות שליליים של לקוחות משמשים כמעין "דרישה" נוספת מהעובדים וככל הנראה מובילים לצורך בהפסקות ארוכות יותר על מנת להתאושש מהחוויה שהם מייצרים אצל העובד. לעומת זאת, רגשות חיוביים פועלים בשני מישורים. ביטוי של רגשות חיוביים על ידי לקוחות מוביל עובדים לקחת הפסקות רבות יותר, ייתכן שכ"פרס" על תפקודם הטוב שנתפס בעיניהם כזה שהוביל לרגשות החיוביים אצל הלקוח. עם זאת, בנוכחות דרישות עבודה גבוהות, ביטוי של רגשות חיוביים על ידי לקוחות מוביל להפסקות <u>קצרות</u> יותר של עובדים. ייתכן וזה מסמל את הירתמותם של העובדים לצורכי המערכת בשעת צורך. ייתכן והירתמות זו מתאפשרת מפני שרגש חיובי של לקוחות מגדיל משאבים פסיכולוגיים בקרב העובדים ובכך מחליף את הצורך בהפסקות ארוכות יותר.

הממצאים שלנו מציעים תמיכה אמפירית חזקה למודל דרישות–משאבי עבודה (Job Demands-Resources), מפני שהשתמשנו במדדים אובייקטיבים ולא חודרניים, בניגוד למחקרי עבר. הממצאים מדגישים את החשיבות במתן תשומת לב גבוהה יותר מצד הנהלות ארגונים לדרישות העבודה ולרגשות שלקוחות מביעים. המחקר מציע כיוונים חדשים להטמעת ניתוח רגשות בתכנון פלטפורמות צ׳אט. למשל, ניתן לנתב לקוחות חדשים לעובדים אשר פחות עמוסים מבחינת דרישות העבודה או לכאלה שנחשפים לביטויי רגשות חיוביים של לקוחות.