The Value of Social Media Customer Support During the Pandemic

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Abstract

Many companies are utilizing social media as the primary avenue for customer service during the pandemic. However, how customers' behaviors and interactions with customer service agents on social media are impacted by the lockdowns has not been well understood. In this study, we examine the impact of lockdowns and physical distancing on changes in customers' behaviors, such as emotional expressions in tweets and customers' satisfaction with social media customer service. Using a difference-in-differences research design, we find that with the lockdowns and physical distancing, customers expressed more negative emotions when tweeting the company they were having issues with. Surprisingly, compared to before the pandemic period, customers' emotional expressions became more positive and they were more likely to express their satisfaction after interacting with customer service agents. Interestingly, our findings reveal that gender differences exist in these scenarios. We also discuss the theoretical and practical implications of these findings.

Keywords: COVID-19 pandemic, customer service, customer complaint, social media, gender differences

1. Introduction

The onslaught of the Coronavirus disease 2019 (COVID-19) pandemic in 2020 affected more than 50 million people and caused unforeseen impacts on individuals, organizations, societies, and governments worldwide. In fact, by spring 2020, more than half of the world's population had been subjected to stay-at-home orders and lockdown enforcements [1]. These lockdowns posed unprecedented impacts on people's lives and various companies' operations.

The lockdowns and physical distancing due to the COVID-19 pandemic also impacted the operations of customer service significantly. Restrictive measures, such as stay-at-home orders, travel bans, and business shutdowns, resulted in call volume surges that overwhelmed call centers [2]. HubSpot's industry data indicate that customer support requests increased exponentially due to the COVID-19 pandemic. From March 2020 to August 2020, customer service support tickets spiked from 6% to over 90% (Forsey, 2021). Meanwhile, businesses were compelled to adapt to remote work due to the lockdown provisions imposed by the government to avoid the transmission of COVID-19. Consequently, in these unforeseen circumstances of the COVID-19 crisis, effectively delivering customer service and fulfilling customers' needs have become key challenges for companies. Agnihotri et al. (2021) noted that in the context of COVID-19, companies could reduce customer retaliation behavior and negative word-of-mouth on social media platforms by effectively dealing with customer complaints. Customer service is vital during times of crisis. As many people are isolated in their homes and experience loneliness, anxiety, and depression, companies find it necessary to deliver customer support with more empathy, care, and concern to fulfill customers' needs. The interaction between customers and companies can boost trust and loyalty to the company [3].

The physical distancing also accelerated the digital transformation of organizations (Boh et al. 2021). The pandemic and associated social distancing restrictions caused many organizations to embrace digital technologies for connecting with customers. Although many companies have already adopted digital technologies before the pandemic, such as using social media channels to sell or promote their brand or provide customer service, whether and how the use of such digital technologies differs during the COVID-19 pandemic versus the time before remains unanswered. Recent work by Wang et al. (2020) noted that most information systems (IS) research about emotional expression focused mainly on two streams, examining the emotion embedded in the text either as

[1] https://www.oecd.org/coronavirus/policy-responses/the-territorial-impact-of-covid-19-managing-the-crisis-across-levels-of-government-d3e314e1/

[2] https://www2.deloitte.com/uk/en/pages/digital-transformation/articles/delivering-customer-service-during-COVID-19.html

URI: https://hdl.handle.net/10125/103069
978-0-9981331-5-7

an antecedent or as an outcome. They also argued that the impact of the external physical environment on users' emotions embedded in the text data remains unclear in the information systems literature. In line with the foregoing, our paper aims to address these gaps and extend our understanding of the impact of COVID-19 on changes in customer behaviors, such as emotional expressions in tweets and customers' satisfaction with social media customer service. Specifically, we aim to answer the following research questions:

1) Did the COVID-19 lockdown impact the emotional expressions in customers' tweets to companies?
2) Did the COVID-19 lockdown impact customers' emotional expressions and satisfaction after engaging with social media customer service agents?
3) If so, did gender differences exist in these scenarios?

To answer these questions, we conducted a field study by collecting data from Twitter. Leveraging the difference-in-differences (DID) research design, we exploited the variations in customers' emotional expressions and satisfaction before and after the COVID-19 pandemic. Our empirical findings reveal that the emotional expressions in customers' tweets were more negative when seeking customer service support on social media during the COVID-19 pandemic. However, the value of social media customer support during the pandemic is that customers were more likely to express satisfaction and positive feelings after interacting with the agents after lockdown. Interestingly, our findings also reveal a gender difference in customer behaviors toward social media customer service during the pandemic.

The rest of the paper is organized as follows. We first discuss the related literature. Next, we present the research setting, data, and measures. We then provide the econometric model specifications, main results, and robustness checks of our main results. In the subsequent section, we perform an additional analysis of gender differences in customer behaviors during the COVID-19 pandemic. Finally, we conclude with a discussion on the implication of our findings.

2. Literature Review: Digital Resilience During COVID-19

The COVID-19 pandemic has not only demonstrated the need for all systems, societies, and organizations to be able to adapt to an unforeseen and challenging disruption but also has had a significant impact on the way people live and work all over the world[3]. Resilience is the capacity that allows a system to adapt to a crisis or disruption while maintaining system function viability or development (Masten, 2013). Digital resilience can be addressed by using digital technologies or information systems to respond to the changes caused by major external shocks, such as the COVID-19 pandemic (Boh et al., 2021). The IS literature on digital resilience during COVID-19 has focused on the effects of remote work on workers' productivity (Tommar et al., 2022), academics' productivity (Cui et al., 2022), and labor market outcomes (Hou et al., 2022), as well as COVID-19's impact on the gig economy and labor market (Basavaraj et al., 2021), e-commerce operations (Han et al., 2021; Hwang et al., 2020), delivery platform on restaurants (Li & Wang, 2020), social media use (Mousavi & Gu, 2021; Rao et al., 2020), and changes in user behaviors on digital platforms (Sim et al., 2022; Singh et al., 2021; Wang et al., 2020).

Another important research focus in the stream of literature is the use of social media on resilience. The usage and consumption of social media surged considerably during COVID-19. In times of crisis or disasters, people use social media to seek information, monitor the situation, express their feelings, engage in crisis communication, and connect and engage with their peers, the government, and other organizations (Abbas et al., 2021; Alexander, 2014; Tsao et al., 2021; Volkmer, 2021). Through this research, we expect to add new perspectives to this stream of literature by examining the changes caused by the COVID-19 pandemic on customers' attitudes and behaviors in the context of social media customer service.

3. Research Design and Data

3.1. Natural Experiment Setting and Data

We collected our data from Twitter. Twitter has become a major customer support channel among social networks in recent years[4]. As reported in a social media survey, 38% of Twitter users prefer to tweet or message customer support than using other customer support channels, such as telephone or email[5]. The president declared a national emergency on March 13, 2020, due to the COVID-19 pandemic[6]. After the national emergency declaration, the majority of states

[3] https://www.mckinsey.com/business-functions/people-and-organizational-performance/our-insights/agile-resilience-in-the-uk-lessons-from-covid-19-for-the-next-normal
[4] https://blog.hubspot.com/service/customer-service-tweets
[5] https://business.twitter.com/en/blog/win-over-customers-with-twitter-customer-care.html
[6] https://www.whitehouse.gov/briefing-room/presidential-actions/2022/02/18/notice-on-the-continuation-of-the-national-

issued stay-at-home orders to protect the health and well-being of residents between mid-March and the beginning of April[7]. Given that the national emergency declaration occurred on March 13, 2020, we collected data from October 1, 2019, to August 31, 2020 (treatment year), including 23 weeks as the pre-treatment period and 24 weeks as the post-treatment period, as our treatment group. Further, we obtained data a year ago during the same calendar date, from October 1, 2018, to August 31, 2019 (control year), as the control group following the Miller et al. (2021)'s and Sim et al. (2022)'s approach. We relied on data between October 1, 2018, to August 31, 2019, to provide a control year that was unaffected by the pandemic but captured the seasonal trend in social media and define "pre" and "post" periods based on a counterfactual treatment date - the same calendar date (month and day) of the national emergency declaration in 2019. Figure 1 illustrates the timeline of our natural experiment setting and the construction of the treatment/control group.

This research design allowed us to empirically pin down the impacts of the lockdowns by comparing the differences in customers' emotional expressions, sentiments, and satisfaction before and after the lockdowns, and between the treatment group and control group. In other words, we calculated the differences of dependent variables in pre-treatment-period and post-treatment-period and compared the differences in treatment year (group) and control year (group).

We used the Twitter API to collect all of the tweets mentioning the official customer service accounts of major telecom carriers in the U.S., including AT&T Cares, Verizon Support, Sprint Care, and T-Mobile Help, between October 1, 2018, to August 31, 2020. The reason why we choose telecom carriers is that telecommunications play an essential role to keep businesses, communities, organizations, and governments operating and connected during the pandemic[8]. The tweets we collected were then consolidated into distinct categories of dialogues. We excluded telecom carrier-initiated dialogues and focused on customer-initiated dialogues. A total of 218,033 dialogues were collected. We also collected timestamps, tweet conversation threads, tweet metadata, and Twitter users' profile information, such as the person's number of followers and number of accounts followed.

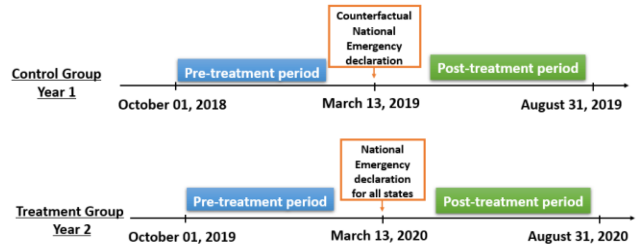

Figure 1. Experiment Setting

3.2. Variables

Our main outcome variables were negative emotions, sentiment changes, and satisfaction. Specifically, the main dependent variables are constructed as follows:

(1) Negative emotions: We measured the negative emotions in tweets using The National Research Council (NRC) Lexicon in Python via the NRCLex package. Notably, several recent research related to COVID-19 have adopted the NRC lexicon to measure textual sentiments and emotions (Aslam et al., 2020; Boon-Itt & Skunkan, 2020; Wang et al., 2020). The NRC emotion intensity lexicon enabled us to examine the expression of eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive) (Mohammad & Turney, 2013). In addition, we identified the basic emotions in the tweets via the NRC lexicon and used these as covariates in the matching (Wang et al., 2020).

(2) Sentiment changes: We followed Hu et al. (2020) approach to constructing sentiment changes and satisfaction measures. We constructed sentiment changes by measuring the sentiment changes between users' first and last tweets. We measured the sentiment score using the 'Emotional tone' in the Linguistic Inquiry and Word Count (LIWC), which can accurately identify emotions in language use (Tausczik & Pennebaker, 2009). LIWC is a popular text analysis tool in social science studies; it has also been applied in numerous works in IS literature related to sentiment analysis (Huang et al., 2017; Kim et al., 2022; Wang et al., 2022; Yin et al., 2014).

(3) Satisfaction: We defined this variable by identifying whether the users expressed gratitude or positive sentiments in the conversation thread after receiving the agents' responses (example: "Thank you for your speedy reply. We will do that.") or if the users clicked "like" to the agents' responses in the conversation thread.

emergency-concerning-the-coronavirus-disease-2019-covid-19-pandemic-2/

[7] https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

[8] https://www.ifc.org/wps/wcm/connect/industry_ext_content/ifc_external_corporate_site/infrastructure/resources/covid-19+impact+on+the+global+telecommunications+industry

Our control variables included variables both at the user level and at the tweet level. The control variables of the user level are the public profile information of each Twitter user, such as the number of tweets posted, followers, likes, people the user followed, user verified badge, and smile expression of the users' profile photos. The control variables of the tweet level are the characteristics of each user-initiated tweet and its conversation thread, such as the word counts of the user-initiated tweet and the length of the tweet conversation threads. Table 1 presents the key variables' summary statistics for the main variables in our dataset.

Table 1. Summary Statistics

Main Variables	Obs	Mean	Std. Dev.
Negative Emotions	218033	.1235	.1871
Sentiment Changes	218033	1.484	20.5377
Satisfaction	218033	.1018	.3024

4. Econometric Analysis and Results

4.1. Model-Free Evidence

We started with the effect of lockdown on customers who contacted a company via social media for support. Figure 2 illustrates the average number of distinct customer-initiated dialogues in the three months before and after the week of Mar 13 (national emergency declaration). This result shows that the use of social media customer service has a slightly increasing trend after the lockdown. We also observed that there is a sharp increase in the number of customers seeking social media customer care in the first two weeks after the lockdown.

Next, we presented a model-free evaluation of the mean differences in negative emotions between the treatment and control groups. Figure 3 shows the time trend of negative sentiments in the three months before and after the week of the national emergency declaration. The vertical line represents the week of Mar 13 (national emergency declaration). It exhibits that after the lockdown started, customers in the treatment group, on average, express more negative emotions in their tweets when they seek support from social media customer service, compared to the control group, indicating an increased negative emotions gap between the control and treatment group. This evidence provides us the preliminary insights into the impact of the COVID-19 lockdown on customers' emotional expressions toward social media customer service.

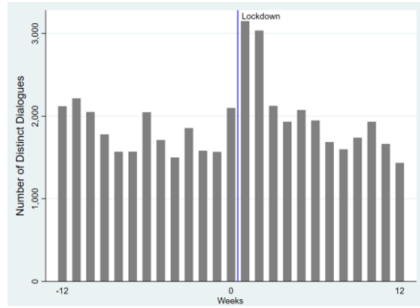

Figure 2. Time Trends of Number of Dialogues

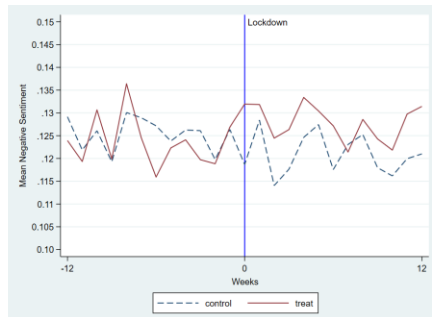

Figure 3. Time Trends of Negative Sentiments

4.2. Lockdowns and Customer Emotions on Social Media

We adopted DID as our main empirical strategy. DID is a popular research design that applies the quasi-experimental approach for estimating natural shocks in empirical economics, social science, and IS research. It is typically used to estimate the causal effect of a specific treatment intervention as long as the parallel pre-trend assumption is fulfilled (Bertrand et al., 2004; Lechner, 2010; Seamans & Zhu, 2013). By using this identification, we can measure the differences in users' negative emotional expressions, sentiment changes between the first and the last tweets, and satisfaction before versus after the lockdown between control and treatment groups. The specification incorporates telecom carrier and week fixed effects, allowing us to effectively control for telecom company-level and week-level unobserved heterogeneities. More specifically, the equation for the DID estimation is as follows:

$$\begin{aligned} DV_{jit} = \beta_0 + \beta_1 Treat_j + \beta_2 Lockdown_t \\ + \beta_3 (Treat_j * Lockdown_t) \\ + Controls + \gamma_t + \delta_i + \varepsilon_{jit} \quad (1) \end{aligned}$$

where DV_{jit} represents three outcome measures, namely, negative emotions, sentiment changes, or satisfaction in a particular tweet posted in year j to telecom carrier i at time t. Herein, j indexes the two-year period (treatment year and control year, Figure 1). The dummy variable $Lockdown_t$ is equal to 1 if week t occurs after the national emergency declaration (that is, the week of March 13, 2020) and 0 otherwise. $Treat_j$ is a dummy variable equal to 1 if a tweet is posted in the treatment year and 0 if a tweet is posted in the control year. The user-level controls include the log number of total tweets, followers, following, likes, verified status, and tweet-level factors containing the tweet word counts and conversation length. γ_t is the time fixed effect, including weekly time dummies that control for time trends. δ_i is the telecom carrier-specific fixed effect that captures the time-invariant characteristics of telecom carrier i, and ε_{jit} is the idiosyncratic error term. Standard errors are robust and clustered at the telecom carrier level. Our main interest is the coefficient of the interaction term β_3, which captures the effect of the lockdown on our main DVs.

The results of the regressions are shown in Table 2. In Column 1, we see that the coefficient of the interaction term Lockdown*Treat is positive, which indicates an increase in negative emotions in the tweets after the lockdown. Next, we examine the impact of the lockdown on sentiment changes between the first tweet and the last tweet. Column 2 in Table 2 shows that the coefficient of Lockdown*Treat is positive and statistically significant, which indicates that since the lockdown began, customers' last tweets have contained more positive emotions after interacting with customer service agents. Furthermore, for satisfaction, we applied a linear probability model (LPM) to the DID setting[10]. The estimation results for the satisfaction are presented in Column 3 of Table 2. The coefficient of Lockdown*Treat is positive and statistically significant, thus providing evidence that the lockdown led to a 1.4% increase in satisfaction. In summary, the COVID-19 pandemic lockdown led to an increase in the negative sentiments of public tweets, but higher customer satisfaction and more positive emotional expressions after customers engaged with the agents. Moreover, during the lockdown and physical distancing period, customers became much happier after interacting with the customer services agent.

Table 2. Impact of COVID-19 on Customer Satisfaction

	(1)	(2)	(3)
	Negative	Sentiment Changes[9]	Satisfaction
Lockdown	.0079**	-.7656	.0139
	(.0018)	(.6614)	(.0069)
Treat	-.0003	-.1881	.0015
	(.0022)	(.1968)	(.0034)
Lockdown*Treat	**.0066****	**.4165****	**.0142***
	(.002)	**(.1068)**	**(.005)**
Controls	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Obs.	218,033	120,850	120,850
R-squared	.0266	.011	.2022

Robust standard errors are enclosed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.3. Threats to Identification

4.3.1. Parallel Trends Assumption. The key assumption of DID is the parallel trend assumption that the trends of outcome variables should remain unchanged between the control and treatment groups in the absence of the treatment, which is unobservable and impractical to test directly (Angrist & Pischke, 2008). To examine whether our data satisfy the parallel trend assumption, we used multiple strategies to provide evidence that the assumption is not likely to have been violated in our setting. We first tested this assumption by conducting a parallel trend analysis similar to that in Cui et al. (2022), Calvo et al. (2020), and Seamans and Zhu (2013). The results show no pre-treatment differences in our main DVs between the treatment and control groups, which validates the parallel trend assumption[11].

Furthermore, we tested the parallel trend assumption by conducting a pre-treatment test (Table 3 Panel A). Meyer (1995) suggested using data in multiple pre-intervention periods to examine validity threats. We operationalized the pre-treatment trend test following Kumar and Telang (2012) approach by setting up a hypothetical treatment date to divide the pre-treatment period into two sub-pre-treatment periods for the treatment and control groups. The results showed no differences in the main DVs of the treatment and control groups before and after the hypothetical treatment date. In sum, the results of the parallel trend test and pre-treatment test support the parallel trend assumption, which eliminates the concern that our main DVs have different trends in the pre-treatment period.

4.3.2. Propensity Score Matching. The sample in our dataset was not randomly selected from all Twitter users. To exclude the possibility that our results were driven by other observable factors between users in the control and treatment years, we adopted DID analysis with propensity score matching (PSM) to obtain a balanced sample and ensure that our treatment and control groups were comparable. Our matching approach was applied at the Twitter user level, and we matched each user in the treatment group to the most

[9] The drop in sample number is due to the fact that not every tweet received agent responses.

[10] The major concerns of LPM are that the predicted probabilities can be greater than 1 or less than 0. In our LPM, more than 90% of the predicted probabilities fell between 0 and 1. We also used the robust standard error to address heteroskedasticity.

[11] The results are not presented in the paper due to space limitation, but available upon request.

similar user in the control group based on the users' profile information and the emotional effects of tweets. The number of matched pair numbers is 59,182 using PSM one-to-one matching with non-replacement. We conducted two-sample t-test results to evaluate the covariates and the quality of the matches and found that after matching, no significant differences for all covariate means were noted in the two groups[12], indicating an effective balance of the treatment and control groups across all covariates (Ho et al., 2007). We then used the matched samples to perform DID analysis using Equation 1. The results of variables of interest still hold after matching (Table 3 Panel B), thus providing further support to our main finding.

Table 3. Panel A: Using December 22, 2020 (2019) as a hypothetical treatment date			
	(1)	(2)	(3)
	Negative	Sentiment Changes	Satisfaction
Lockdown	.0056	3.3006	-.0274**
	(.0062)	(1.559)	(.007)
Treat	-.0002	-.3385	.0012
	(.0017)	(.3519)	(.0056)
Lockdown*Treat	**-.00001**	**.187**	**.0002**
	(.0032)	**(.2838)**	**(.005)**
Controls	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Obs.	110,677	61,833	61,833
R-squared	.024	.0117	.21
Table 3. Panel B: DID estimates on PSM sample			
	(4)	(5)	(6)
	Negative	Sentiment Changes	Satisfaction
Lockdown	.0096*	-1.2451	.0059
	(.0041)	(1.6357)	(.0112)
Treat	-.0007	-.2423	-.00003
	(.0023)	(.1858)	(.0038)
Lockdown*Treat	**.0078****	**.4795****	**.0152***
	(.0017)	**(.0853)**	**(.006)**
Controls	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Obs.	181,877	101,496	101,496
R-squared	.0273	.0113	.2025
Robust standard errors are enclosed in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

4.3.3. Time Variation Estimations. In this section, we summarized results from two different time variations estimations. First, in our main analysis, we used data from October 1 to August 31. Since most States terminated stay-at-home orders before June 2020[13], we used data from October 1 to June 2 and the significant effects persist (Table 4 Panel A). Second, most States issued lockdown and stay-at-home orders in response to the COVID-19 outbreak between Mar 19 and Mar 31, 2020[14]. To avoid complications associated with a partially COVID-19 impacted month, we used data that excluded the last two weeks in March from the sample. The results of negative sentiments and sentiment changes still hold after we omitted the data in late March (Table 4 Panel B). Overall, our results are consistent with the main results.

Table 4. Panel A: Using October 1 – June 2 sample			
	(1)	(2)	(3)
	Negative	Sentiment Changes	Satisfaction
Lockdown	.0087**	-.9402	.0067
	(.0024)	(.7523)	(.0077)
Treat	-.0001	-.2233	.0014
	(.0022)	(.2155)	(.0036)
Lockdown*Treat	**.0053***	**.8079****	**.0264****
	(.0019)	**(.2389)**	**(.0049)**
Controls	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Obs.	159,124	88,644	88,644
R-squared	.0256	.0114	.2052
Table 4. Panel B: Exclude sample in late March			
	(4)	(5)	(6)
	Negative	Sentiment Changes	Satisfaction
Lockdown	.008**	-.7932	.015
	(.0018)	(.6261)	(.0072)
Treat	-.0003	-.186	.0015
	(.0022)	(.2037)	(.0034)
Lockdown*Treat	**.0066****	**.4622*****	**.0121**[15]
	(.002)	**(.0316)**	**(.0056)**
Controls	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Obs.	207,335	115,094	115,094
R-squared	.0266	.0107	.203
Robust standard errors are enclosed in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

5. Addressing Alternative Explanations

One lingering concern here is that the changes in customers' emotions and satisfaction on social media are due to customer service agents behaving abnormally during the COVID-19 pandemic. For example, customer service agents feel stressed during

[12] Detailed mean differences before and after PSM are available upon request.

[13] https://ballotpedia.org/States_that_issued_lockdown_and_stay-at home_orders_in_response_to_the_coronavirus_(COVID-19)_pandemic,_2020

[14] https://ballotpedia.org/States_that_issued_lockdown_and_stay-at home_orders_in_response_to_the_coronavirus_(COVID-19)_pandemic,_2020

[15] P-value=0.12

the pandemic, thus affecting their sentiments in customer service tweets. Or a large amount of customer service requests intensifies agents' workload and extends the response time, thus leading to increased customers' negative emotions. To rule out the possibility that the agents behave differently leads to our main findings, we examine agent behavior before and after the lockdown by re-estimating the DID model of equation (1) with the agent's sentiments, response time, and the conversation length as outcome variables. If the customer service agents behave differently after the lockdown, the coefficient of Lockdown*Treat would be significant. Table 5 indicates that there are no significant differences in customer service agents' behaviors and the conversation length before and after the lockdown.

Table 5. Addressing Alternative Explanation

	(1)	(2)	(3)
	Agent's Sentiment	Response time (sec)	Conversation Length
Lockdown	-3.0168*	1189.7899	-.0255
	(.9805)	(1790.1656)	(.0568)
Treat	-1.5731	1812.3801	-.0266
	(2.4686)	(1342.9914)	(.0301)
Lockdown*Treat	**.1242**	**3922.3433**	**.0668**
	(.5883)	**(2900.9513)**	**(.0436)**
Controls	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Obs.	120,850	120,850	120,850
R-squared	.0079	.046	.8011

Robust standard errors are enclosed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Additional Exploration: Gender Differences

Previous studies have shown that the COVID-19 pandemic has a stronger impact on women's psychological stress and mental health (Ausín et al., 2021; García-Fernández et al., 2020; Hou et al., 2020; Yıldırım et al., 2021). The psychological stress for females, compared with their male counterparts, is not only from the physical distancing and lack of social connectedness but also from the surge of domestic burdens, such as childcare and house chores (Ausín et al., 2021; Cui et al., 2022; Power, 2020; Tommar et al., 2022). Thus, we conjecture that the impact of lockdown has led female users more likely to express negative emotions.

To test the conjecture, we employed two strategies to evaluate whether a such difference exists in social media customer services, and if so, to what extent. First, we tested gender differences by performing an analysis similar to Cui et al. (2022). We only used the data around the actual lockdowns between October 1, 2019, and August 31, 2020. We also excluded users with an unidentifiable gender in this analysis, resulting in 41,569 samples (19,635 females and 21,934 males). Following Cui et al. (2022), the treatment group in this analysis comprised only female users, whereas the male users served as the control group. Such that, gender is the only the difference between treatment group and the control group. Additionally, we defined the "pre-treatment" and "post-treatment" periods according to the national emergency declaration on March 13, 2020. Thereafter, we compared negative emotions and sentiment changes, between female and male users before and after the outbreak of the COVID-19 pandemic using the following model specification:

$$DV_{jit} = \beta_0 + \beta_1 Female_j + \beta_2 (Female_j * Lockdown_t) + Controls_{jit} + \gamma_t + \delta_i + \varepsilon_{jit} \quad (2)$$

where DV_{jit} represents negative emotions and sentiment changes of a particular tweet posted by gender j to telecom carrier i at time t. The dummy variable $Lockdown_t$ equals 1 if week t occurred after the national emergency declaration (the week of March 13, 2020) and 0 otherwise. $Female_j$ is a dummy variable equal to 1 if a tweet was posted by a female user and 0 otherwise. Other variables are the same as the baseline DID model in Equation (1). The variable of interest is the coefficient on the two-way interaction term β_2, which captures the impact of the lockdown on female users related to male users' tweeting behaviors. We didn't find evidence supporting that females are more negative when tweeting the companies they were having issues with. (Table 6 Column 1). However, compared to their male counterparts, the satisfaction level of females increases less, measured by sentiment changes, after interacting with customer service agents (Table 6 Column 2).

A similar pattern is observed when we adopt the DDD specification (Bertrand et al., 2004; Greenwood & Wattal, 2017) of our primary sample with data in the control year. Similarly, we excluded users with unidentifiable genders in this analysis, resulting in 89,600 samples (41,914 females and 47,686 males). Then, we estimated the following model speciation to investigate whether the impact of the pandemic lockdown differed across genders:

$$DV_{jit} = \beta_0 + \beta_1 Lockdown_t + \beta_2 Treat_t + \beta_3 Female_j + \beta_4 (Lockdown_t * Female_j) + \beta_5 (Lockdown_t * Treat_i) + \beta_6 (Treat_i * Female_j) + \beta_7 (Lockdown_t * Treat_i * Female_j) + Controls_{jit} + \gamma_t + \delta_i + \varepsilon_{jit} \quad (3)$$

where DV_{jit} refers to negative emotions and sentiment changes of a particular tweet posted by gender j to telecom carrier i at time t. $Female_j$ is a dummy variable equal to 1 if a tweet was posted by a female user and 0 otherwise. Lockdown, Treat, and Control variables, week dummies, telecom carriers dummies, and error terms are the same as those in Equation 1. The impact of the lockdown on female users versus male users is captured by the three-way interaction term β_7 . The heterogeneous effect on gender is reported in Column 3 and Column 4 of Table 6. The results echo that although no apparently more negative emotions were found in female users' posts, the sentiment changes dropped by 0.86 after the lockdown compared with male users. Across two empirical specifications, our evidence on gender difference consistently shows female customers are not posting more negative when they initially sought customer service support, but their satisfaction level is less likely to be improved after interacting with customer service agents, compared with their male counterparts.

7. Discussion and Conclusion

Our results demonstrate that customers tweet more negatively when they sought customer service support on social media during the pandemic. Surprisingly, customers expressed more positive emotions and they were more likely to express satisfaction after interacting with customer service agents. More interestingly, our findings also reveal that though female customers are not posting more negatively when they initially sought customer support from the companies, but their satisfaction level is less likely to be improved after interacting with customer service agents, compared with male customers.

Table 6. Gender Difference Analysis and DDD Analysis of Gender

	(1)	(2)	(3)	(4)
	Negative	Sentiment Changes	Negative (DDD)	Sentiment Changes (DDD)
Lockdown			.0174**	-2.0039
			(.0049)	(.8859)
Treat			.0041	-.8474*
			(.0019)	(.3014)
Female	-.0077	.5778**	.0089**	.1307
	(.0082)	(.1613)	(.0027)	(.1266)
Lockdown * Female	**-.0036**	**-.6085***	-.0023	.3666
	(.0099)	**(.2268)**	(.0017)	(.1855)
Lockdown * Treat			.0057**	1.289*
			(.0014)	(.5156)
Treat* Female			-.0056**	.5375**
			(.0017)	(.16)
Lockdown*Treat* Female			**.0032**	**-.8666***
			(.0029)	**(.2959)**
Controls	Yes	Yes	Yes	Yes
Telecoms FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Obs.	41569	23,931	89600	51,119
R-squared	.0078	.0025	.0274	.0143

Robust standard errors are enclosed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This study contributes to two important streams of literature. First, to the best of our knowledge, this research is among the early studies investigating to what extent the COVID-19 outbreak altered the attitudes and behaviors of customers in the context of social media customer service. We contribute to the growing literature on the impact of COVID-19 policies on changes in customer behaviors on digital platforms by demonstrating that during the COVID-19 lockdown, customers expressed more negative emotions when tweeting the companies they were having issues with. Furthermore, after the customers interacted with the customer service agents, their emotional expressions became more positive, and they were more likely to express their satisfaction with the agents.

Second, this work contributes to the small but growing literature on IS about customer complaints and customer service on social media platforms. Our work contributes to this stream by investigating the impacts of the COVID-19 pandemic on customers' emotional expressions and satisfaction in the context of social media customer service. This study provides empirical evidence demonstrating the resilience of social media customer service during a pandemic.

The current study also offers essential managerial insights for practitioners. An interesting finding of this study is that customers were more likely to express positive emotions and satisfaction after engaging with customer service agents during the pandemic. Notably, when agents replied to the customers' tweets to address their concerns or complaints, the connection and engagement between customers and agents fostered online social connectedness that relieved feelings of social isolation and loneliness during the lockdown (Khosravi et al., 2016; Moore & March, 2022). This demonstrates the value of social media customer service in a time of the pandemic. Hence, in order to provide good customer service experiences in the post-pandemic, companies should efficiently respond to customers' complaints or queries and effectively handle their issues or concerns rather than ignoring customer complaints on social media.

References

Abbas, J., Wang, D., Su, Z., & Ziapour, A. (2021). The Role of Social Media in the Advent of COVID-19 Pandemic: Crisis Management, Mental Health Challenges and Implications. *Risk Management and Healthcare Policy, 14*, 1917–1932.

Agnihotri, D., Kulshreshtha, K., & Tripathi, V. (2021). Emergence of social media as new normal during COVID-19 pandemic: a study on innovative complaint handling procedures in the context of banking industry. *International Journal of*

Innovation Science, *ahead-of-print* https://doi.org/10.1108/IJIS-10-2020-0199

Alexander, D. E. (2014). Social Media in Disaster Risk Reduction and Crisis Management. *Science and Engineering Ethics*, *20*, 717–733.

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Aslam, F., Awan, T. M., & Syed, J. H. (2020). Sentiments and emotions evoked by news headlines of coronavirus disease (COVID-19) outbreak. *Humanities and Social Sciences Communications*, *7*.

Ausín, B., González-Sanguino, C., & Castellanos, M. Á. (2021). Gender-related differences in the psychological impact of confinement as a consequence of COVID-19 in Spain. *Journal of Gender Studies*, *30*(1), 29-38.

Basavaraj, N., Foutz, N. Z., & Li, B. (2021). *Resilience of the U.S. Gig Economy during the COVID-19 Pandemic: Insights from Location Big Data* Forty-Second International Conference on Information Systems, Austin.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, *119*(1), 249-275.

Boh, W. F., Constantinides, P., & Padmanabhan, B. (2021). Digital Resilience During Covid: Fleeting or Enduring. Forty-Second International Conference on Information Systems, Austin.

Boon-Itt, S., & Skunkan, Y. (2020). Public Perception of the COVID-19 Pandemic on Twitter: Sentiment Analysis and Topic Modeling Study. *JMIR Public Health Surveillance*, *6*(4).

Calvo, E., Cui, R., & Wagner, L. (2020). Disclosing Product Availability in Online Retail. *Manufacturing & Service Operations Management*, *0*(0).

Cui, R., Ding, H., & Zhu, F. (2022). Gender Inequality in Research Productivity During the COVID-19 Pandemic. *Manufacturing & Service Operations Management*, *24*(2), 707-726. https://doi.org/10.1287/msom.2021.0991

Forsey, C. (2021). *How COVID-19 Impacted Customer Service & What's Next [Data + Expert Tips]*. HubSpot. Retrieved April 14 from

García-Fernández, L., Romero-Ferreiro, V., Padilla, S., & López-Roldán, P. D. (2020). Gender differences in emotional response to the COVID-19 outbreak in Spain. *Brain and Behavior*, *11*(1).

Greenwood, B. N., & Wattal, S. (2017). Show Me the Way to Go Home: An Empirical Investigation of Ride-Sharing and Alcohol Related Motor Vehicle fatalities. *MIS Quarterly*, *41*(1), 163-187.

Han, B. R., Sun, T., Chu, L. Y., & Wu, L. (2021). COVID-19 and E-commerce Operations: Evidence from Alibaba. Forty-Second International Conference on Information Systems, Austin.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis*, *15*, 199-236.

Hou, F., Bi, F., Jiao, R., Luo, D., & Song, K. (2020). Gender differences of depression and anxiety among social media users during the COVID-19 outbreak in China:a cross-sectional study. *BMC Public Health*, *20*.

Hou, J., Liang, C., Chen, P.-Y., & Gu, B. (2022). Does Telework Reduce Unequal Impacts of the COVID-19 Disaster on Job Losses Across Genders? In. Available at SSRN: https://ssrn.com/abstract=4038594 or http://dx.doi.org/10.2139/ssrn.4038594.

Hu, Y., Gal, D., & Tafti, A. (2020). Please Don't Feed the Trolls: The Role of Customer Politeness in Customer Service Engagement on Social Media. In *Working Paper*. University of Illinois at Chicago.

Huang, N., Hong, Y., & Burtch, G. (2017). Social Network Integration and User Content Generation: Evidence from Natural Experiments. *MIS Quarterly*, *41*(4), 1035-1058.

Hwang, E. H., Nageswaran, L., & Cho, S.-H. (2020). Impact of COVID-19 on Omnichannel Retail: Drivers of Online Sales during Pandemic. In. Available at SSRN: https://ssrn.com/abstract=3657827 or http://dx.doi.org/10.2139/ssrn.3657827.

Khosravi, P., Rezvani, A., & Wiewiora, A. (2016). The impact of technology on older adults' social isolation. *Computers in Human Behavior*, *63*, 594-603.

Kim, K., Park, J., Pan, Y., Zhang, K., & Zhang, X. M. (2022). Risk Disclosure in Crowdfunding. *Information Systems Research*, *0*(0).

Kumar, A., & Telang, R. (2012). Does the Web Reduce Customer Service Cost? Empirical Evidence from a Call Center. *Information Systems Research*, *23*(3-part-1), 721-737. https://doi.org/10.1287/isre.1110.0390

Lechner, M. (2010). The Estimation of Causal Effects by Difference-in-Difference MethodsEstimation of Spatial Panels. *Foundations and Trends in Econometrics*, *4*(3), 165-224. https://doi.org/10.1561/0800000014

Li, Z., & Wang, G. (2020). The Role of On-Demand Delivery Platforms in Restaurants during Disruption: Evidence from the Coronavirus Pandemic. In. Available at SSRN: https://ssrn.com/abstract=3665798 or http://dx.doi.org/10.2139/ssrn.3665798.

Masten, A. S. (2013). Global Perspectives on Resilience in Children and Youth. *Child Development*, *85*(1), 6-20.

Meyer, B. D. (1995). Natural and Quasi-Experiments in Economics. *Journal of Business & Economic Statistics*, *13*(2), 155-161.

Miller, A. R., Segal, C., & Spencer, M. K. (2021). Effects of COVID-19 Shutdowns on Domestic Violence in US Cities. In *NBER Working Paper No. 29429* National Bureau of Economic Research, Inc.

Mohammad, S., & Turney, P. (2013). Crowdsourcing a Word–Emotion Association Lexicon. *Computational Intelligence*, *29*(3), 436-465.

Moore, K. A., & March, E. (2022). Socially Connected during COVID-19: Online social connections mediate the relationship between loneliness and positive coping strategies. *Journal of Stress, Trauma, Anxiety & Resilience*, *1*(1).

Mousavi, R., & Gu, B. (2021). The Effect of Resilience Messaging on Community Conformity to Government Healthcare Guidelines: An Empirical Analysis of Governors' Twitter Use During COVID-19 Pandemic. Forty-Second International Conference on Information Systems, Austin.

Power, K. (2020). The COVID-19 pandemic has increased the care burden of women and families. *Sustainability: Science, Practice and Policy*, *6*(1).

Rao, H. R., Vemprala, N., Akello, P., & Valecha, R. (2020). Retweets of officials' alarming vs reassuring messages during the COVID-19 pandemic: Implications for crisis management. *International Journal of Information Management*, *55*.

Seamans, R., & Zhu, F. (2013). Responses to entry in multi-sided markets: The impact of craigslist on local newspapers. *Management Science*, *60*(2), 476-793.

Sim, J., Cho, D., Hwang, Y., & Telang, R. (2022). Frontiers: Virus Shook the Streaming Star: Estimating the COVID-19 Impact on Music Consumption. *Marketing Science*, *41*(1), 19-32.

Singh, S. P., Yadav, P., & Qiao, Z. (2021). Penguin Has Entered the Home: The Impact of COVID-19 Induced Work From Home on Open Source Software Development. Forty-Second International Conference on Information Systems, Austin.

Tausczik, Y. R., & Pennebaker, J. W. (2009). The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. *Journal of Language and Social Psychology*, *29*(1), 24-54. https://doi.org/10.1177/0261927x09351676

Tommar, S. A., Kolokolova, O., & Mura, R. (2022). When Paid Work Gives in to Unpaid Care Work: Evidence from the Hedge Fund Industry Under COVID-19. *Management Science*, *0*(0).

Tsao, S.-F., Chen, H., Tisseverasinghe, T., Yang, Y., Li, L., & Butt, Z. A. (2021). *What social media told us in the time of COVID-19: a scoping review* (Lancet, Issue.

Volkmer, I. (2021). *Social Media and COVID-19: A global study of digital crisis interaction among Gen Z and millennials*.

Wang, X., Jiang, M., Han, W., & Qiu, L. (2022). Do Emotions Sell? Impact of Emotional Expressions on Sales in Space-Sharing Economy. *Production and Operations Management*, *31*(1), 65-82.

Wang, X., Mousavi, R., & Hong, Y. (2020). The Unintended Consequences of Stay-at-Home Policies on Work Outcomes: The Impacts of Lockdown Orders on Content Creation. In. Available at SSRN: https://ssrn.com/abstract=3739572 or http://dx.doi.org/10.2139/ssrn.3739572.

Yıldırım, M., Çiçek, İ., & Şanlı, M. E. (2021). Coronavirus stress and COVID-19 burnout among healthcare staffs: The mediating role of optimism and social connectedness. *Current Psychology*, *40*, 5763–5771.

Yin, D., Bond, S. D., & Zhang, H. (2014). Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews. *MIS Quarterly*, *38*(2), 539-560.