Does Customers' Emotion toward Voice-based Service AI Cause Negative Reactions? Empirical Evidence from a Call Center

Bin Li
Harbin Institute of Technology
libin_jx@126.com

Luning Liu
Harbin Institute of Technology
liuluning@hit.edu.cn

Weicheng Mao
Harbin Institute of Technology
weicheng.mao@gmail.com

Yongcuomu Qu
Harbin Institute of Technology
qycm@hit.edu.cn

Abstract

Many companies are introducing voice-based artificial intelligence (AI) into their call centers. Little is known about the relationship between customers' emotions to voice-based AI service and customers' negative reactions. This study investigates the link between customers' emotions toward voice-based AI service and customers' negative reactions. Our results reveal that customers' emotion toward voice-based AI service could significantly affect their complaint behavior, and customers' complaints differ among emotion types. Customers' negative and positive emotions toward voice-based AI services have a significantly negative and positive effect, respectively, on customer complaint behavior than neutral emotions. We also find that the exchange round of human-computer interaction moderates the effect of the customer emotion by attenuating its effect on customer complaints. This study investigates the impact of customers' emotions toward voice-based AI service on customers' complaint behavior to make up the existing research insufficiency in a certain degree.

1. Introduction

Artificial intelligence (AI), a new high-tech, has become popular and a topic of interest in the modern service industry [1]. AI has great commercial value [2] and a brighter future. AI is becoming a major concern for academia and enterprise circles [3], and omnipresent. AI would bring extensive changes that will also affect all aspects of our society and life [4]. Voice-based AI service, one of the major AI applications, is a new popular AI application with unpredicted business potential [4]. It is mainly applied in the service industry, especially in the call center of the telecom company. Call center is an essential part of business, with dramatic effects on the economy [5]. Further, a call center is a very labor-intensive operation, and its overall operating budget is mainly occupied by the cost of staff members who handle phone calls [6].

With the rapid increase in customers and the explosive growth of data, companies' call centers face an enormous challenge in the provision of services. Therefore, more managers turn first to introduce voice-based AI services to provide several unique business benefits. First, the service of AI agent is more efficient than the human agent: it can respond quickly to the customer's service request to reduce the waiting time and improve efficiency [7]. Moreover, voice-based AI service is more stable and available [8], and has strong capabilities of data processing [9]. AI applications, as a self-service technology, can offer 24-hour uninterrupted service. Last but not least, AI applications have broad application foreground and practical value [10, 11]. AI can help firm to reduce the service costs [12], reduce the costs of predictions [13], and increase firm value [14]. Despite these benefits of the voice-based AI service, customer experience to the service and negative reactions are unknown. Contrary to humans, AI has no empathy for the encounter of customers. AI applications cannot respond to customers' emotions. However, emotion plays an important role in communication, and it has a significant relationship with behavior [15]. Prior research has not examined the concrete effects of customers' emotion to voice-based AI service on customers' negative reaction is largely lacking. Formally, this study fills the gap in the literature by focusing on the effects of customers' emotions toward the voice-based AI service on customers' negative reactions. Specifically, we address the following research questions:(1) Do customers' emotions toward AI affect their complaint behavior? (2) How do customers' complaints differ among different emotion types? (3) How do

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the effects of customers' emotions on customer complaint behavior vary for different customers and service experiences?

In this study, the research questions are answered by an empirical study. We address the above research questions using a unique data set relating to voice-based AI service introduction by a large telecom company. The company's call center introduced the AI service to replace its interactive voice response (IVR) agent on January 15, 2019. We collected the conversation's data between the customer and voice-based AI service in February. After dropping some anomalous data, we obtained 285106 conversation records. We use the RoBERTa model [16] to extract the emotion from the conversation texts. Finally, we obtained 25205 positive emotion records, 20060 negative emotion records, and 239841 neutral emotion records. Moreover, we conduct a series of robustness tests to verify the reliability of results.

Our results reveal that customers' emotion toward AI could significantly affect their complaint behavior, and their complaints differ among different emotion types. Customers' negative emotions toward voice-based AI service have a significantly negative effect on customer complaint behavior, and customers' positive emotions have a significantly positive effect on customer complaint behavior than customers' neutral emotions. We also find that the exchange round of the human-computer interaction moderates the effect of the customer emotion by attenuating its effect on customer complaints. Furthermore, our results are robust to probit regression, tobit regression model analysis, and other robust checks.

2. Literature review

2.1. AI in services

AI is increasingly utilized in services and plays an important role in service innovation and revolution [17]. AI applications are increasingly used in frontline services [18] and in reshaping service [1, 19]. AI brings many advantages, including efficacy and accuracy [20], and it provides many valuable chances for academic achievement. Hence, many scholars are increasingly exploring the relationship among AI, customers, and employees [21]. A wealth of information system research has investigated the impact of AI applications on service, marketing and management.

Existing research on AI in services mainly focus on two aspects. The first aspect is the study on the effect of AI on customers. AI-based service technology can influence customers' experience [22]. For example, anthropomorphic consumer robots can make consumers feel warm [23]. AI service quality has a significant influence on customer satisfaction and loyalty [24] and its technology can influence customers' behavior [25]. The second aspect is the study on the effect of AI on employees. AI technology can predict service agent stress from emotion's patterns in service interactions [26]. Employees and AI actively complement each other [27]. Augmenting service employees with AI improved employees' performance in interpersonal emotion regulation [28]. AI has a positive effect on employee engagement [29].

Although the literatures research achievements based on AI were sprung up, the amount was simply inadequate, especially in voice-based AI. Existing research mainly focuses on the advantages of AI across various fields [9]. However, the negative impact of AI on customers is largely lacking, especially in service. Our work aims to extend the literature of the negative reactions (e.g., customer complaints) resulting from AI applications.

2.2. Emotion in services

Emotion is a collection of psychological states that include subjective experience, expressive behavior, and peripheral physiological responses [30]. Many studies indicate that emotion plays a vital role in service, and it is a central element in understanding customers' experiences and behavior [31, 32]. Generally, the existing emotion can be categorized as positive emotion, neutral emotion and negative emotion [33]. Emotion and behavior were highly associated [34]. Emotion has an important impact on customer behaviors, including repurchase, complaining, and loyalty [35]. Negative emotions act as mediators between service performance and complaint behavior [32]. Management of emotions is very important for managers [36]. Although many scholars have investigated the impact of customer emotion on customer behaviors, they have focused on the scenario of customers to human employees. An interesting topic that garners attention is whether the relationship between customer emotion and behavior in a traditional context is still suitable for customers and AI service. Our work extends this literature by providing empirical evidence for the impact of customers' emotions toward voice-based AI service on customer behavior.

2.3. Customer complaint in service

A customer complaint is a very common phenomenon in the service industry and a key factor of firm management [37]. Firms often spend a number of resources responding to customer complaints [38]. Customer complaints may cause serious problems, including reducing loyalty [38], reducing satisfaction, evaluation, and purchase behavior [39], increasing in the probability that the customer stops buying [40]. The quality of customer service is an important factors that affect customer complaint [41]. Most studies on customer service focus on frontline employees' handling of customer complaints. For example, the customer service delivered by the employees would influence revisiting intentions of consumers [42]. Retail and other service personnel apologize for products are defective or service delivery fails could reduce customer complaints [43]. Therefore, customer complaint management is increasingly important [37]. Customer complaint management can help firm to lower the cost and improve service quality [44]. Different complaint-handling initiatives would have different effects [45]. Therefore, the key to customer complaint management is to explore the influential factors that could influence customer complaint behavior.

Previous studies show that customer complaints can be induced by many factors such as interactional justice [46], service failure [47], customers' emotion toward human employees [48], and AI technology [8]. However, a few studies focus on the impact of customers' emotions toward voice-based AI service on customer complaint behavior. This study aims to fill this gap.

3. Empirical methodology and analysis

3.1. Background

The data for this research were taken from a telecom firm's call center, which offers mobile communication services such as broadband and voice services to individual customers through its communications infrastructure and technologies. This firm is a well-known telecom company in China, and it has plenty of customers. As the need for customer service increases, the service capability and operating costs of the call center face a great challenge. Therefore, reducing operating costs and improving service quality become the prime assignment of call center managers. The growth in AI applications provides ample potential for managers, especially labor-intensive sectors or firms. In this background, the company implements a sophisticated voice-based AI service in its call center to improve service and reduce operating costs. Unlike traditional interactive voice response (IVR) agents that only handle simple inquires with prerecorded messages, voice-based AI service is based on machine learning that enhances communication with customers. Customers can consult about things such as setting a new account, deleting an account, checking money, and malfunction of devices. When receiving customer requests, a voice-based AI service will respond to the message correspondingly, and customers may be transferred to human agents for more information.

3.2. Emotion extraction

In this study, our main aim is to investigate the impact of customers' emotions toward voice-based AI service on customer complaint behavior. First, we analyze the emotions expressed through conversational texts by using emotion analysis technology, which is a classification technology based on natural language processing (NLP). In computer science, many scholars have proposed a sentiment classification model based on deep learning, which has achieved good results. Many scholars have studied the language representation models based on NLP. These models include the ELMo method [49], the Generative Pre-trained Transformer (GPT) method [50], the Bidirectional Encoder Representations from Transformers (BERT) method [51], and the RoBERTa model [16]. Combined with the research purpose, we select the RoBERTa model to extract the emotions from the conversation texts. RoBERTa model integrates the advantages of the BERT model and the transformer model. The transformer model obtained better results.

3.3. Data and variables

The observation duration in our study is 28 days from February 1, 2019 to February 28, 2019. Our dataset contains timestamps of customer behavior (i.e., customer call-in and complaint time). Customers' basic information (i.e., age, gender, open-time, location), behavior information (complaint or not), emotion polarity, call length, and interaction rounds are included in the dataset. We operationalized customer complaints [44] as our dependent variable, as a binary variable indicating whether customer complaints after finish human-AI conversation. We measure this variable by observing customers' complaint records: complaint score 1 and no complaints score 0. For independent variables, we use RoBERTa model to recognize emotions; we divide these emotions into three types (positive, negative, neutral) and we use three binary variables to represent them. For control variables, we consider customers' age, gender, open-time, location, call length, and exchange rounds. The variables such as gender and location can be observed from the call center database directly, and the variables such as age, open-time, call length, and exchange rounds.

In this study, we operationalized customer complaints as a dependent variable, a binary variable indicating whether a customer complains after their conversation with the AI is complete. We measured this variable by observing customers' complaint records and assigned it a value of "1" if the customer complains and "0" if otherwise. We recognized emotions as independent variables and divided them into three types: "negative", "neutral" and "positive", to define two binary variables representative of the customers' emotional states. We noticed that complaints constituted only 0.58% of the conversation records, suggesting that finding complaints in our dependent variable (complaint) would be a rare event. Among binary logit regression analysis, the rare events would lead to biases [52]. To avoid misclassification, we need to use some approaches to solve the imbalance problem. Some methods can deal with the imbalance problem; these methods include SMOTE [53] and RandomUnderSampler [54]. After considering the advantages and disadvantages of these methods, we opted for the RandomUnderSampler. Finally, we obtained 9990 samples, comprising 1665 complaints and 8325 non-complaints.

4. Econometric identification and estimation models

The model-free results based on the data across the three conditions in Table 1 suggest that customers with negative emotions toward voice-based AI service have higher complaint rates than those with positive emotions and neutral emotion. Specifically, the positive emotion group has a 0.8% complaint rate, the negative emotion group has a 26.05% complaint rate, and the neutral emotion group has 17.25%.

Table 1. Model-Free results

Emotion	N	Customer complaint rate
positive emotion	748	0.8
neutral emotion	8501	17.25
negative emotion	741	26.05

We present the magnitude of the effects in Figure 1. Compared with neutral emotions, negative emotions increase customer complaint rates dramatically by 51.01% (from 17.25 to 26.05). We conducted a correlation analysis and found that this variable does not exist as a serious multicollinearity problem. Next, we apply econometric models to test the effects. We develop a logit model:

$$Complaint\ likehood_i = \frac{Exp(U_i)}{Exp(U_i)+1} \qquad (1)$$

$$U_i = a + a_1 * positive\_emotion_i + a_2 * negative\_emotion_i + \Phi Controls_i + \varepsilon_i \quad (2)$$

Where U_i denotes the latent utility of making a complaint, and the dependent variable of the complaint denotes whether the customer has a complaint after the end of the interaction with voice-based AI service. The key independent variables are positive emotion$_i$ and negative emotion$_i$; they are binary variables. Both positive emotion$_i$ and negative emotion$_i$ are dummy variables used to represent the customers' three emotions. The neutral emotion is the benchmark. Controls$_i$ is a vector of control variables with individual customer profiles and operational data, including age, gender, open-time, location, call length, and rounds of human-computer interaction.

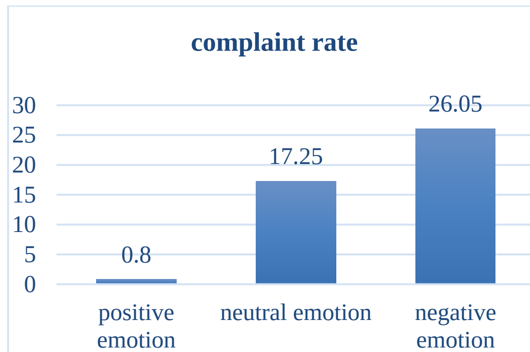

Figure 1. Complaint rates across emotions

4.1. Propensity score matching

In the previous section, we use the sampling technique to deal with the imbalance problem of samples. However, there may exist another problem that the bias caused by self-selection is out of our control. The group's standard is based on the type of emotion (neutral emotion, positive emotion, and negative emotion), and the emotion of conversation records is affected by other factors (e.g., customers' feature and event feature), which drive conversation records into a particular treatment group. Therefore, we use propensity score matching [55] to deal with the self-selection bias. We match each record with negative emotion or positive emotion to a record with neutral emotion based on the 1:1 nearest neighbor algorithm with replacement.

4.2. Rosenbaum bounds sensitivity analysis

Propensity score matching has one important limitation because it depends on the observable characteristics can account for selecting records into the treatment and control groups. However, some unobservable characteristics also would induce bias. Therefore, we use the rosenbaum bounds sensitivity analysis [56] to measure how strongly an unobservable must influence the selection process. It can show these bounds on the odds ratio for the two matched samples:

$$\frac{1}{\tau} \leq \frac{\frac{p_i}{1-p_i}}{\frac{p_j}{1-p_j}} \leq \tau \quad (3)$$

The p_i denotes the complaint probability of a record with non-neutral emotion (positive emotion and negative emotion), and p_j denotes the complaint probability with no neutral emotion. Γ measures the level of selection effects from unobservable variables. This method suggests that Γ should be close to 1 if the unobservable variable does not play a significant role in selection.

5. Results and robustness checks

5.1. Main findings

In regression analysis, we use balance samples (after under-sampling) and unbalance samples (origin samples) as our data separately. The logit, probit, and tobit regressions are performed. Table 2 shows the regression results of logit, probit, and tobit; they suggest that customer emotion is significant to a complaint behavior. Specifically, both balance and unbalance samples show that a customer with negative emotion is much more likely to complain than a customer with neutral emotion, and a customer with neutral emotion is much more likely to complain than a customer with positive emotion.

We divided the three types of emotion's data into two groups: Group A and Group B. Group A includes negative and neutral emotions, while Group B includes positive and neutral emotions. We use PSM to deal with the self-selection problem. Table 3 displays comparisons for the groups. Table 3 has Column A and Column B, corresponding with the treatment of a negative emotion record and a positive emotion record. A neutral emotion is matched with a negative emotion or positive emotion, according to the covariates mentioned above (age, gender, location, open year, rounds, and call length). Of the 1241 records with treated cases, 26.05% of records in Group A were found to have a complaint. Of the non-treated cases in Group A, only 6.76% made a complaint. Since the t-test value is equal to -10.37, controlling for the observed differences between the treatment and control groups, records with negative emotion are more likely to make a complaint. Table 3 shows a similar analysis for the other treatment (positive emotion) in Columns B. To deal with the bias due to unobservable characteristics, the last row in Table 3 shows the results of the Rosenbaum bounds analysis. Table 3 also shows that the percentage of complaints between treated cases and not treated cases is significantly different between the groups. We report the critical values of Γ at which the complaint effect becomes insignificant. The Γ values of Group A and Group B are 1.2 and 1.5. If an unobservable variable wants to nullify the effect of non-neutral (negative or positive) emotion on customer complaint behavior, it would have to change the odds of selection into the treatment group by at least 20 percent.

5.2. Heterogeneity effects

The results of the moderation effects are shown in Table 4. Customer attributes have no moderation effects. According to the results in Table 5, the rounds moderate the customer's emotion toward voice-based AI service by attenuating its effect on complaint behavior. Thus, the more rounds of human-computer interaction, the less likely the complaint. One possible explanation for this result is that the familiarity of voice-based AI service increased with the rounds of human-computer interaction. Therefore, customers are much more likely to adapt and accept the voice-based AI service, resulting in fewer complaints.

5.3. Robust check

5.3.1. Evidence using an additional dataset

In addition to a sample of 285106 conversation records of February in our main analyses, we collect additional data on another sample of 328380 conversation records of March. We repeat the analyses for this sample using the above methods, and we find consistent results for this alternative sample. Table 6 reports these estimates.

5.3.2. Removal of outliers

Our second robustness check involves the sensitivity analysis with the outliers in the demographics and interactive data removed to avoid readers assuming that the effect may be due to the outliers in data. To perform this check, we remove those records whose values are greater than 99.5% and replicate the whole analysis. Table 7 reports the results for the removal of outliers. We find that similar findings are derived, proving that our estimation of the effects is unlikely to suffer from this data issue.

Table 2. Emotion impact on customer complaint rate

	Balance samples (after under-sampling)			Unbalance samples (origin samples)		
DV: complaint	Logit	Probit	Tobit	Logit	Probit	Tobit
Positive emotion	-2.37***	-1.130***	-0.08***	-2.368***	-0.751***	-0.003***
Negative emotion	1.04***	0.603***	0.148***	0.941***	0.347***	0.006***
Controls	Y	Y	Y	Y	Y	Y
Robust	Y	Y	N	Y	Y	N
Constant	-0.086	-0.183***	0.33***	-3.556***	-2.000***	0.012***
N	9990	9990	9990	285106	285106	285106
Log likelihood	-4018.76	-4029.32	-3930.96	-9652.18	9668.17	329844.68
(Pseudo) R2	0.1072	0.1048	0.0889	0.0559	0.0543	-0.0012

Note: ***, ** and * represent significance at the 1%, 5%, and 10%level, respectively

Table 3. Propensity score matching and rosenbaum bounds sensitivity analysis

Treatment	A group	B group
Number of matched cases	1482	1496
Percentage of complaints among treated cases	26.05%	0.8%
Percentage of complaints among not treated cases	6.76%	6.15%
Diff Mean	19.29%	5.35%
t-test (Diff Mean > 0)	-10.37***	5.7***
Diff Mean (Std. Err)	0.193	0.053
Std.Dev.	0.370	0.183
Rosenbaum upper bounds significant for Gamma (Γ)	1.2	1.5

Note: ***, ** and * represent significance at the 1%, 5%, and 10%level, respectively

Table 4. The moderation effects of customer attributes

	Complaint (Emotion:1=Positive,0=Neutral)		Complaint (Emotion:1=Negative,0=Neutral)	
Condition 1. Moderation Effects of Age	Coef.	Z	Coef.	Z
Emotion	-2.912	-1.94	1.04	1.53
Emotion*Age	0.004	0.13	0.0085	0.62
Condition 2. Moderation Effects of Gender	Coef.	Z	Coef.	Z
Emotion	-2.464***	-4.59	1.539***	6.42
Emotion*Gender	-0.986	-0.86	-0.249	-0.68
Condition 3. Moderation Effects of Open year	Coef.	Z	Coef.	Z
Emotion	-2.274***	-2.73	1.272***	3.56
Emotion* Open year	-0.057	-0.73	0.023	0.62
N	1492		1482	

Note: ***, ** and * represent significance at the 1%, 5%, and 10%level, respectively

Table 5. The moderation effects of service experiences

	Complaint (Emotion:1=Positive,0=Neutral)		Complaint (Emotion:1=Negative,0=Neutral)	
Condition 4. Moderation Effects of Rounds	Coef.	Z	Coef.	Z
Emotion	3.46	1.78	2.592***	5.53
Emotion* Rounds	-1.439**	-2.35	-0.179***	-2.66
Condition 5. Moderation Effects of Call Length	Coef.	Z	Coef.	Z
Emotion	0.0373	0.02	2.291***	3.94
Emotion* Call Length	-0.05	-0.98	-0.009	-1.54
N	1492		1482	

Note: ***, ** and * represent significance at the 1%, 5%, and 10%level, respectively

Table 6. Propensity score matching and rosenbaum bounds sensitivity analysis

Treatment	A group negative	B group positive
Number of matched cases	2100	1924
Percentage of complaints among treated cases	23.5%	0.87%
Percentage of complaints among not treated cases	6.69%	5.38%
Diff Mean	15.1%	4.5%
t-test (Diff Mean > 0)	-11.05***	5.86***
Diff Mean (Std. Err)	-0.168	0.008
Std.Dev.	0.358	0.170
Rosenbaum upper bounds significant for Gamma (Γ)	1.23	1.15

Note: ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively

Table 7. Emotion impact on customer complaint rate

	Balance samples (after under-sampling)			Unbalance samples (origin samples)		
DV:complaint	Logit	Probit	Tobit	Logit	Probit	Tobit
Positive emotion	-2.646***	-1.207***	-0.063***	-	-	-
Negative emotion	-	-	-	1.482***	0.787***	0.164***
Controls	Y	Y	Y	Y	Y	Y
Robust	Y	Y	N	Y	Y	N
Constant	0.637	-0.045	0.133***	-1.390***	-0.795***	0.259***
N	1402	1402	1402	1404	1404	1404
Log likelihood	-180.84	-179.33	437.98	-547.8	-549.5	-524.6
(Pseudo) R2	0.1212	0.1286	-0.0559	0.1362	0.1335	0.1382

Note: ***, ** and * represent significance at the 1%,5%, and 10% level, respectively

6. Discussion

This study focuses on the relationship between customer emotions toward voice-based AI service interactions and customer complaint behavior. Our results reveal that customers' emotions could significantly affect their complaint behavior, and their complaints differ among different emotion types. More specifically, customers' negative emotions toward voice-based AI service have a significantly negative effect on customer complaint behavior, and positive emotions have a significantly positive effect on customer complaint behavior compared with customers' neutral emotions. The most plausible explanation is that customers attribute their emotional experience of interaction to the company; therefore, compared with customers with neutral emotions toward voice-based AI service, customers with negative emotions toward voice-based AI service have a higher complaint rate. We also find that the exchange round of human-computer interaction moderates the effect of the customer emotion by attenuating its effect on customer complaints. Thus, the more rounds of human-computer interaction, the less likely the customer will complain. Our research has made up the existing research insufficiency in a certain degree and provided a strong support for the follow-up research.

6.1. Theoretical and practical implications

This study extends frontline service research in at least three important aspects. First, it extends the literature on customer emotion and AI service. Previous studies mainly focused on customers' emotions toward employees (human agents) (e.g., [26],[32],[57]), and how to use the AI to measure or analyze customer emotions [26, 28]. However, the impact of customers' emotions on AI service remains deficient in the literature. To our best knowledge, our study is among the first to empirically test the impact of customers' emotions toward voice-based AI service on customers' behavior in the service industry.

Second, we extend the literature on the negative reactions toward the AI service. Previous studies mainly focused on the benefit of the AI service. For example, some scholars found that AI can improve purchase behavior [58], enhance clinical diagnosis and decision-making performance [59], and increase international trade [60]. However, the impact of AI services and negative reactions should be researched more. We use the customer complaint to measure the negative reaction of AI, and we investigate the negative impact of service AI using a unique data set relating to voice-based AI service introduction by a large telecom company.

Third, this study further complements the literature of call centers and new technology by investigating voice-based AI services in call centers. Existing research mainly focuses on the optimization algorithm and strives to solve the steady-state optimized operation model of queue more rapidly, reliably, and efficiently [61,62]. Several studies investigate the impact of new technology on customer behaviors in the call center [8, 63]. Our work is among the few studies that focus on the relationship between AI service and customer behavior in call centers.

Our findings also have important practical implications. First, we provide support to business decision-makers seeking a trade-off between the benefits and drawbacks of AI introduction to their customer service platforms. The trend of marketization of AI service seems irresistible, hence more of AI service is available on the market. Novel technology is a "two-edged sword"; the matter must be considered dialectically for an enterprise. Second, we make important implications regarding the design of voice-based AI service applications (e.g., we improve emotional recognition and product-related responsibilities). Voice-based AI service products directly contact customers; full consideration of the impact of customer emotions in the design of AI service delivery schemes is vital for the commercialization of AI voice products. Third, our research finds that customers' emotions could influence their complaint behavior. Prior research also indicates that AI needs to understand people's emotional status and respond appropriately in the future [1]. Our finding could help firm managers to develop an effective emotion regulation strategy for AI service.

6.2. Limitations and future study

The main goal of this study was to understand customer complaint behavior by examining the relationship between customer emotions toward voice-based AI service and complaint behavior. Our study focuses on the impact of the customer emotion experience on customer complaints instead of the interaction between the consumer and AI voice. The study contributes to our understanding of explicit consumer emotion to customer complaint encounters. However, our work is subject to some limitations. First, we focus on the impact of AI implementation at the company level, but future researchers may benefit from including the call center employee's perspective. Second, we conducted this study based on a single company, so our results may not be universally applicable. More analyses with multiple firms are needed to generalize our findings. Future research should consider the impact of AI on work and its related aspects to the design considerations of AI in the workplace. In addition, future research should explore the impacts of AI on employee's behavior, especially the dark sides of AI on human agent.

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