Walking a Fine Line: Customer Participation in Live Streaming Reminder

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Abstract

Reminder messages play a vital role in customer relationship management. Previous e-mails and short messages have received a lot of attention. However, it is not clear how the reminder message in the academic live streaming affects customer participation. In this paper, we explore the influence mechanism of reminder messages in the live streaming platform based on logistic regression and hidden Markov model (HMM). The analysis results suggest that the reminder message has positive effects on participation while "technostress" causes the inverted U-shaped effect between the reminder frequency and customer participation. In addition, compared with working hours, the reminder message has a greater impact on participation when the corresponding live streaming is during after-work hours. The impact of reminder message wears off as the customer's usage level of the platform increases. This study not only contributes to customer relationship management, but also has practical significance for academic live streaming platforms.

Keywords: reminder message; live streaming; customer relationship management; technostress; hidden Markov model

1. Introduction

With the advent of the digital age and the popularization of live streaming technology, academic live streaming is gradually playing an important role in academic exchanges. It contributes to knowledge dissemination and knowledge sharing (Boncori, 2020). According to a report of Meticulous Research[1], the total scale of the live streaming industry has reached $4.29 billion in 2021. Among them, live streaming in the field of knowledge sharing is becoming an important component and new growth point, accounting for 13% share and 15.8% annual average growth rate in the live streaming market. However, the competition of academic live streaming platforms in the market also brings challenges to live streaming service providers (Wongkitrungrueng et al., 2020). On the basis of ensuring the quality of their own content, academic live streaming platforms need to conduct good customer relationship management to gain long-term competitive advantages (Zhang et al., 2020).

The use of reminder messages as an important means of customer relationship management plays a vital role in motivating customers' participation (Pop-Eleches et al., 2011). Previous studies have found that emails, push notifications and short messages have a positive effect on customer participation. For example, Merisavo and Raulas (2004) suggested that email can significantly promote user loyalty and facilitate further purchase. Notifications (Hao, 2019) and short messages (Phang et al., 2019) have also been found to have a positive effect on customer participation. However, there are some concerns about the negative effect of excessive push messages. According to a survey of 200 mobile apps and thousands of users (SWRVE 2021)[2], more than 45% of the CRM methods (such as push email, messages) are turned off directly by users, and 37% of users said that notifications did not contribute to their experience.

To better understand the value of reminder messages in academic live streaming, we gathered data from a leading online medical academic live streaming platform. Leveraging this dataset, we examine how reminder messages affect users' participation in the academic live streaming platform. We specified our model based on logistic regression and hidden Markov model (HMM). The results

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[1] https://www.meticulousresearch.com/product/live-streaming-market-5225

[2] https://www.swrve.com/resources/weblog/the-state-of-retail-2021-responding-to-2020

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showed that reminder messages have positive effects on customer participation, while “technostress” causes the inverted U-shaped effect between the reminder frequency and customer participation. In addition, compared with working hours, the reminder message has a greater impact on participation when the corresponding live streaming is during after-work hours. The impact of reminder message wears off as the customer’s usage level of the live streaming platform increases.

This study contributes to the research streams on customer relationship management and academic live streaming. It refines the influence mechanism of reminder messages. In addition, it also has practical significance for academic live streaming platforms. It provides insights on whether to set reminder messages and their appropriate frequency. And it gives personalized advice to the platforms for setting reminder messages according to the heterogeneity of users and live time.

2. Literature Review

2.1 Customer Relationship Management

Generally speaking, customer relationship management (CRM) refers to companies’ various methods to coordinate the interaction with their customers on products and services in order to retain users and prevent user loss (Netzer et al., 2008). Existing literatures have studied CRM methods in various scenarios, focusing on how it directly or indirectly affects user participation and retention, and have given strategies to generate revenue for companies by optimizing CRM. The research contexts include online deal services (Ascarza et al., 2018), re-targeted advertising (Sahni et al., 2019), donation (Gopalakrishnan et al., 2017) and different ad formats (Abhishek et al., 2012). In recent years, with the popularization of mobile apps, more personalized and instant methods have attracted the widespread attention of researchers. Kumar et al. (2014) studied how email clicks and opens affect the timing of user opt-in and opt-out and the average purchase amount of users. Phang et al. (2019) studied how mobile short messages with different frequencies affect the user's psychological perception and proposed the corresponding push strategy. Zhang et al. (2019) and Luo et al. (2014) also provided insights on mobile CRM and its advantages and challenges.

Compared with the other types of CRM methods, the reminder message is widely used by companies due to its moderate intrusion and concise content. It stands for a kind of remind as a pop-up message in the message list in mobile apps, and the content of the reminder is mainly about recent events of the apps. However, previous studies about the reminder message are relatively scarce. Pop-Eleches et al. (2011) was the first to propose the concept of reminder in short message service (SMS). Ghose et al. (2021) used the concept of "reminder message" to study the impact of different types of reminders on users' health concepts and willingness to consult doctors. However, the impact of the reminder message on user behavior and its internal mechanisms have not been fully explained like other CRM methods.

Overall, the existing research on the effects and mechanisms of CRM methods is relatively comprehensive. However, there is still little research on reminder messages in academic live streaming platforms, and there is no in-depth research on their influence on user behavior. In this paper, we study the effects and influence mechanisms of reminder messages and provide a new research perspective of customer relationship to influence future CRM research.

2.2 Technostress

Previous literature has argued that stress emerges from the combination of the individual and her/his environment (Lazarus and Folkman 1984). Cooper et al. (2001) emphasized that stress is a dynamic subjective experience manifested as adverse reactions related to stressors. As a key component of stressors, IT has attracted attentions of researchers in recent years, and the concept of "technostress" has been proposed (Tarafdar et al., 2019). Numerous studies have shown that the most common sources of technostress are invasion, overload, and uncertainty (Ayyagari et al., 2011). These stressors are essentially adverse consequences brought about by various designs and functions of information systems, such as fatigue and role confusion caused by page content, privacy protection, push notifications, etc. (Salo et al., 2022).

In related CRM research, similar technostress presented an "inverted U-shaped" effect quantitatively. Zhang et al. (2017) and Luo and Kumar (2013) have discovered this nonlinear effect and observed its variance in different states, but their researches did not explore this phenomenon further. Other studies have explained this nonlinear effect from the perspectives of over-targeting (Hao, 2019), multi-stage of consumers (Abhishek et al., 2012), and privacy concerns (Goldfarb and Tucker 2011; Tucker, 2014). We believe that whether the consideration is of privacy or information overload, it can be interpreted as a kind of pressure on the individual's psychology. Combined with the concept of "technostress", we will focus on the expected impact that high-frequency reminder messages may bring. At the same time, based on the state analysis of HMM, we will deeply explore the heterogeneity of this technostress under different customer relationship, and provide a more comprehensive elaboration of this phenomenon.

3. Hypotheses Development

3.1 Main Effects of Reminder Messages

In the long practice of the industry, customer relationship management (CRM) has taken a variety of forms, that have a positive effect on customer participation (Ascarza et al., 2018; Kumar et al., 2014; Zhang et al., 2019). Merisavo and Raulas (2004) found that email marketing can significantly improve customers' attitudes towards brands, and customers are more likely to recommend these email messages to their friends. Bonfrer and Drèze (2009) utilized a risk model to study the optimal frequency and timing of email delivery to promote customer relationships. Netzer et al. (2008) used a hidden Markov model to capture user behavior dynamics. Their results indicated that regular email push has a significant promoting effect on alumni's choice to participate in donation activities. The reminder message, as a new form of CRM, can also stimulate user engagement (Chen et al., 2022). Therefore, we propose the following hypothesis.

H1a. The reminder message is positively associated with participation.

The effect of reminder messages is not immutable. Taking "technostress" into account, the too frequent use of technology could serve as a source of invasion and uncertainty in users' lives, which can lead to repulsion and disgust on the part of the users (Salo et al., 2022). Previous researches support this point from different aspects. Ascarza and Hardie (2013), and Ascarza et al. (2018) explored the impact of email push on user churn, and the results showed that users' positive response to email doesn't always lead to users' active participation, on the contrary, positive responders may become "silent churn". Tucker (2014) pointed out that too much mobile app push will make users disable notifications, resulting in unnecessary marketing costs. Hao (2019) proposed the concept of "over-targeting", which reveals the negative effects of excessive information push in the mobile scene. In this paper, we posit that excessive reminder messages may backfire. Hence, we assume that:

H1b. The inverted U-shaped relationship exists between the cumulative reminder message and participation.

3.2 Moderating Effects of Live Time and Customers' Usage Level

Early studies suggested that when people utilize IT to complete work or participate in social affairs, IT will change their allocation of time accordingly (Lee, 1999; Green, 2002). Some studies have focused on the effect of time of day on user behavior. Sherman et al. (1995) introduced the concept of "dayparting" into the display of customized advertising, that is, dividing the day into different time periods and adopting different marketing strategies. Beyers (2004) and Veglis (2014) further investigated the heterogeneity of customer behavior among different time of day. Phang et al. (2019) further explained the effectiveness of push based on time distribution. Their experiment proves that the optimal pushing time is different between the two value appeals of hedonic/utilitarian. In this paper, similarly, we suggest that the time zone of live streaming affects doctors' responses to reminder messages. Following Zhang et al.(2021), we denote the time after 18:00 as the time of night and after-work activities (after-work hours), during which doctors have spare time to arrange their lives or choose to improve their professional quality. Therefore, we tend to assume that reminder message is more effective when the corresponding live streaming is during after-work hours. Hence, we propose the following hypothesis.

H2. Compared with working hours, the reminder message has a greater impact on participation when the corresponding live streaming is during after-work hours.

Other studies have focused on the usage level of platforms and services. The main results suggested that, with other conditions fixed, increasing use time will reduce the user's interaction with the platform. For example, Parsons and Ralph (2014) found that cumulative use time negatively moderates user engagement behavior in recommendation systems. Turel and Serenko (2012) found that users who have been registered on social platforms for a longer time interact less frequently. Studies often attribute this insensitivity to familiarity and knowledge of the platform (Ko and Dennis 2011), which further leads to more personalized decisions (Williams and Pollock, 2012). In this paper, similarly, we argue that the longer users use the platform, the more they become familiar with the functions and the less they respond accordingly to reminder messages.

H3. Customers' usage level negatively moderates the impact of the reminder message on participation.

4. Research Context and Data

4.1 Data

To address the above research questions from an empirical perspective, we collected data from one of the largest medical live streaming platforms in China, which provides high-quality professional discussion opportunities and knowledge for doctors and patients. The data we obtained covers a span of about 5 months from January to June, 2021. It includes the basic information of particular live streams and users, the details of user participation behavior and reminder messages.

The original data included 15,034 records of user participation, 12,270 records of user information, and 233 records of live stream. According to the platform's settings, users will be included in the platform's reminder list once they create an account on the platform. As the time, speaker and other detailed information of a live streaming are determined, the platform would send the reminder messages to specific users. This reminder message mainly contains the accurate time and keynote speakers' information of the live stream.

After deleting the user records with duplicate information, we constructed a data set containing 233 live streaming records and 11,767 users records. The data set described the situation of users receiving reminder messages and participating in live streaming in detail, and the number of total records was 1,637,180. Specifically, the final data set includes the user id, the time of creating the account, the start and end time of watching live streaming, the user type, the region, and whether the user has received the reminder message. It also includes the id, type, speaker information, starting and ending time, and location information of every selected live stream.

4.2 Variables and Descriptive Statistics

In this paper, we study the impact of reminder messages on user participation in academic live streaming platforms, as well as the moderating effect and the inner influence mechanism. Specifically, we defined the binary independent variable *Reminder* as whether the user is reminded according to the time and department. We also defined *Num_reminder* as the cumulative number of reminder messages a user received. In the construction of the dependent variable, we defined the binary variable *Participation* as whether the user entered the live stream.

Considering the moderating effect, we took the time zone of live stream and the cumulative use time of users as moderating variables, which are represented by *Live_time* and *User_tenure* respectively. In addition, we defined the corresponding control variables of *Live_type, User_type, Length, Speaker_num, Position and Region_match.* Among them, *Live_type* represents whether the live streaming is specialized or not. *User_type* represents whether the user is a doctor. *Length* refers to expected duration of the live streaming. *Speaker_num* is the number of speakers in the live streaming. *Position* is the title of the speaker. *Region_match* refers to region consistence between the live streaming and users. The detail explanation of each variable is shown in Table1.

Table 1. Variable descriptions

Variables	Descriptions
Reminder	A binary variable indicating whether the user is reminded (Yes: 1, No: 0).
Num_reminder	Cumulative number of reminder messages.
Participation	A binary variable indicating whether the user entered the live streaming (Yes: 1, No: 0).
Live_time	A binary variable that represents the time zone of live streaming (Later than 18:00: 1, Others: 0).
User_tenure	The cumulative use time since the user created account (in months).
User_type	A binary variable that represents user type (Doctor: 1, Others: 0).
Live_type	A binary variable that represents live type (Specialized live: 1, Others: 0).
Length	The expected duration of the live streaming (in hours).
Speaker_num	The number of speakers in the live streaming.
Position	The title of the speaker. (Chief physician: 3; Associate chief physician: 2; Others: 1). The highest title is taken when the number of speakers is more than one.
Region_match	Whether the user's region matches the region of the live streaming (Yes:1, No: 0)

At the same time, we report the results of descriptive statistical analysis of the variables in Table

2. The results showed that the proportion of physician users is higher, and the proportion of new and old users (*User_tenure*) is balanced. The expected time and speakers of the live streaming are also relatively uniform. The proportion of users' receiving reminders and participation are relatively low.

To make the whole structure of paper more clear, we specified the above data processing procedure and the construction of research models in Figure 1.

5. Analyses and Results

5.1 Effects of Reminder Messages on User Participation Behavior

Table 2. Descriptive statistics

Variables	Count	Mean	SD	Min	Max
Reminder	1637180	0.122	0.327	0	1
Num_reminder	1637180	1.861	6.754	0	59
Participation	1637180	0.0918	0.154	0	1
Live_time	1637180	2.247	2.452	0	12
User_tenure	1637180	0.829	0.376	0	1
User_type	1637180	0.848	0.359	0	1
Live_type	1637180	0.872	0.334	0	1
Length	1637180	1.115	0.351	0.5	3
Speaker_num	1637180	2.342	1.115	1	7
Position	1637180	2.535	0.595	1	3
Region_match	1637180	0.114	0.318	0	1

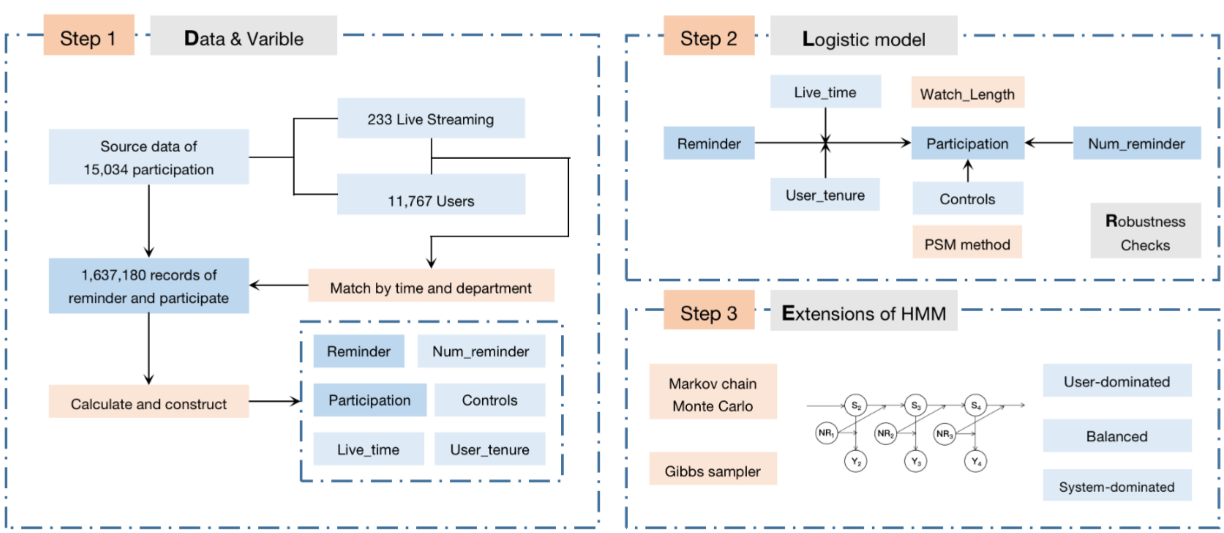

Figure 1. Specified research framework

We study the impact of the reminder message on user participation and the moderating effect, so as to verify H1, H2 and H3. Specifically, considering that *Participation* is a binary variable, we use a Logistic regression model to explore the relationship between the reminder message and user participation behavior.

Live_type, User_type, Length, *Speaker_num*, *Position*, and *Region_match* are the control variables.

According to Hypothesis H1a, Model 1 is constructed to study the linear effect of the reminder message on participation (see Table 3). According to Hypothesis H2 and H3, we construct Model 2, which mainly explores the moderating effect on the impact of the reminder message (see Table 4). The effects of the moderating variables individually and jointly are expressed by Model 2A, Model 2B and Model 2C respectively.

According to H1b, we construct Model 3, which mainly explores the nonlinear effect of cumulative reminder messages on user participation, in which the cumulative reminder messages *Num_reminder* is independent variable (see Table 3).

Table 3. Effects of reminder messages on user participation behavior

Variables	**Model 1**	**Model 3**
Reminder	0.931^{***} (0.025)	
Num_reminder		0.420^{***} (0.004)
Num_reminder^2		-0.040^{*} (0.001)
Live_time	0.140^{***} (0.023)	0.116^{***} (0.023)
User_tenure	-0.061^{***} (0.001)	-0.064^{***} (0.018)
Live_type	0.420^{***} (0.032)	0.398^{***} (0.033)
User_type	-0.233^{***} (0.054)	-0.102^{*} (0.052)
Length	0.660^{***} (0.020)	0.664^{***} (0.020)
Speaker_num	-0.114^{***} (0.010)	-0.104^{***} (0.009)
Position	0.274^{***} (0.017)	0.296^{***} (0.017)
Region_match	2.601^{***} (0.045)	2.610^{***} (0.045)
Constant	-7.231^{***} (0.081)	-7.245^{***} (0.083)
Observations	1,637,180	1,637,180

Standard errors in parentheses are robust and clustered by user id.
*** p<0.01, ** p<0.05, * p<0.1

According to construction of the above model, we analyze data in STATA16.0 software. It can be seen that the existence of reminder messages has a significantly positive impact on users' live streaming participation (ß$_{11}$=0.931, p<0.01), and the impact of cumulative reminder messages on users is nonlinear, indicating an inverted U-shaped relationship (ß$_{31}$=0.420, ß$_{32}$=−0.040, p<0.1). That is, when a user has received less than 5.25 reminders, that user's participation increases with the increase of reminders, but when a user has received more than 5.25 reminders, that user's participation decreases with the increase of reminders. These results are consistent with the results of Tucker (2014) and Hao (2019), which also indicate that the concept of "technostress" is applicable to the impact of reminder messages on user experience: excessive interaction will weaken the promotion effect of the interaction itself. H1a and H1b are supported.

Table 4. Moderating effects

Variables	**Model 2A**	**Model 2B**	**Model 2C**
Reminder	0.833^{***} (0.045)	1.087^{***} (0.040)	0.983^{***} (0.058)
Live_time* Reminder	0.121^{**} (0.050)		0.133^{***} (0.049)
User_tenure* Reminder		-0.002^{***} (0.001)	-0.002^{***} (0.001)
Live_time	0.107^{***} (0.027)	0.144^{***} (0.023)	0.108^{***} (0.027)
User_tenure	-0.061^{***} (0.017)	-0.044^{**} (0.018)	-0.044^{**} (0.018)
Live_type	0.425^{***} (0.033)	0.419^{***} (0.033)	0.425^{***} (0.032)
User_type	-0.233^{***} (0.053)	-0.235^{***} (0.053)	-0.235^{***} (0.053)
Length	0.661^{***} (0.020)	0.658^{***} (0.020)	0.659^{***} (0.020)
Speaker_num	-0.114^{***} (0.010)	-0.113^{***} (0.010)	-0.113^{***} (0.010)
Position	0.275^{***} (0.017)	0.272^{***} (0.017)	0.273^{***} (0.017)
Region_match	2.606^{***} (0.044)	2.604^{***} (0.043)	2.604^{***} (0.044)
Constant	-7.211^{***} (0.082)	-7.258^{***} (0.081)	-7.236^{***} (0.081)
Observations	1,637,180	1,637,180	1,637,180

Standard errors in parentheses are robust and clustered by user id.
*** p<0.01, ** p<0.05, * p<0.1

From Table 4, it can be concluded that the interaction term between *Live_time* and *Reminder* is positively significant (ß$_{24}$=0.133, p<0.01). That is to say, under the same reminder messages condition, the user is more likely to participate in the live stream if the live stream is during after-work hours. Hence, H2 is supported. While the interaction term between *User_tenure* and *Reminder* is negatively significant (ß$_{25}$=-0.002, p<0.01). That is to say, under the same reminder messages condition, the shorter the cumulative use time, the more likely the user is to participate in the live stream. Hence, H3 is also supported.

5.2 Robustness Checks

To check whether our model results are robust, we conduct robustness checks in several ways below. First of all, we change our measurement of the dependent variable to test whether the main influence effect still holds. For the behavior of user participation, we use *Watch_length*, which indicates users' length of time viewing the live stream, as the dependent variable to replace *Participation* (whether users participate in the live stream). The regression results are shown in Table 5.

The results show that the linear and nonlinear effects of reminder messages remain significant, and that the estimated coefficients of the moderating variables are also consistent with our main results. This indicates that our measurement of variables in the original model is reasonable, and the analysis results would not vary significantly among different ways of measuring variables.

Table 5. Regression results of Watch_length

Variables	**Model 1**	**Model 2**	**Model 3**
	Watch Length	Watch Length	Watch Length
Reminder	0.930*** (0.021)	0.983*** (0.045)	
Num_reminder			0.427** (0.004)
Num_reminder^2			-0.039* (0.001)
Live_time* Reminder		0.133*** (0.052)	
User_tenure* Reminder		-0.002*** (0.001)	
Live_time	0.140*** (0.026)	0.108*** (0.027)	0.136*** (0.020)
User_tenure	-0.061*** (0.001)	-0.044*** (0.013)	-0.167*** (0.016)
Live_type	0.420*** (0.038)	0.425*** (0.030)	0.458*** (0.041)
User_type	-0.233*** (0.050)	-0.235*** (0.043)	-0.172*** (0.041)
Length	0.660*** (0.019)	0.659*** (0.019)	0.870*** (0.020)
Speaker_num	-0.114*** (0.010)	-0.113*** (0.013)	-0.241*** (0.011)
Position	0.274*** (0.011)	0.273*** (0.012)	0.409*** (0.009)
Region_match	2.606*** (0.045)	2.604*** (0.042)	3.014*** (0.043)
Constant	-7.231*** (0.080)	-7.236*** (0.079)	-8.756*** (0.081)
Observations	1,637, 180	1,637, 180	1,637, 180

Standard errors in parentheses are robust and clustered by user id.
*** p<0.01, ** p<0.05, * p<0.1

Secondly, sample selection bias is possible in this study. We cannot affirm that reminder messages are sent to users on a completely random basis, as no random field experiment is conducted in our study. In this context, propensity score matching (PSM) was used to test the selection bias of samples.

The core idea of propensity score matching (PSM) is to find those individuals who are similar in various dimensions, and then analyze the results based on these matched individuals, so as to minimize the influence of individual characteristics on the main model results. Firstly, on the user dimension, we have selected *User_tenure*, *User_type* and *Region_match* to be part of our propensity matching score. Only when these variables are controlled can reminder messages be shown to be random among users. Secondly, after the calculation of propensity score, we used 1:1 nearest neighbor matching, kernel matching and nearest-neighbor matching with caliper (1:3) to match the samples and selected the caliper (1:3) with the best matching effect as the final method. After dropping 73,532 samples that are not matched, we re-conducted regression analysis of models 1-3 and the results are shown in Table 6. It can be seen that the effect of reminder messages is still consistent with the conclusion before, which indicates that the deviation of sample selection in the original data is limited. In general, the effect of reminder messages and the moderating effects in this paper are not affected by variable measures, model, or sample selections, manifesting the robustness of our findings.

Table 6. Regression results after PSM

Variables	**Model 1**	**Model 2**	**Model 3**
Reminder	1.013*** (0.040)	2.069*** (0.051)	
Num_reminder			0.242*** (0.008)
Num_reminder^2			-0.027** (0.001)
Live_time* Reminder		0.384*** (0.036)	
User_tenure* Reminder		-0.020*** (0.003)	
Live_time	0.341*** (0.029)	0.344*** (0.021)	0.575*** (0.018)
User_tenure	-0.018*** (0.001)	-0.052*** （0.018)	-0.125*** (0.012)
Live_type	0.913*** (0.030)	0.939*** (0.028)	1.049*** (0.024)
User_type	-0.317*** (0.047)	-0.181* (0.055)	-0.350** (0.052)
Length	0.660*** (0.029)	0.968*** (0.032)	1.103*** (0.028)
Speaker_num	-0.281*** (0.011)	-0.482*** (0.020)	-0.587*** (0.014)
Position	0.793*** (0.014)	0.803*** (0.016)	0.670*** (0.019)
Region_match	3.285*** (0.059)	3.273*** (0.061)	3.305*** (0.055)
Constant	-8.652*** (0.090)	-10.859*** (0.085)	-10.571*** (0.085)
Observations	1,563,648	1,563,648	1,563,648

Standard errors in parentheses are robust and clustered by user id.
*** p<0.01, ** p<0.05, * p<0.1

5.3 Extensions

Based on the above analysis, the direct impact of reminder messages on user participation has been comprehensively demonstrated, but the specific mechanism of it has not been fully explained.

To address this problem, we propose a hidden Markov model (To support this contribution, we have made all code available on github[3]). Specifically, we defined the relationship between the user and the platform as a hidden state and make the time series correspond one-to-one to each live stream. Considering the continuity and robustness of our model, we targeted the sample at 1731 users who stayed on the platform for the whole period. As for model estimation, we adopted Markov chain Monte Carlo (MCMC). And Gibbs sampler and Metropolis-Hastings algorithm were used for our hierarchical Bayesian model. We performed a total of 50,000 iterations and discarded 40,000 sampling results as "burn-in" samples. Following the method proposed by Gelman and Rubin (1992), we find that on the three parallel chains, the latent scale reduction factors (PSRFs) for all parameters are less than 1.2, which indicates that the model has achieved convergence. Additionally, the value of deviation information index (DIC) reaches its minimum when there're three hidden states.

In theory construction, we creatively introduced "Human-Tech Dominance" for explanation of hidden relationship states. "Human-Tech Dominance "is a concept summarized from Latour's (1996) theory of actor networks and the definition of dominant and submissive character by Nass et al. (1995). We think that the customer relationship could be concretized as the relationship between the user and the platform, showing anthropomorphic characteristics. The relationship is always dominated by one side, and the other side's behavior is more affected and more likely to change.

Since Netzer et al. (2008) demonstrated the disadvantages of static models and proposed using HMM to describe user relationships, the application of HMM in relationship management has been widely promoted (Abhishek et al., 2012; Zhang et al., 2017). Although such definitions do explain overall behavioral trends, it does not account for the heterogeneity of users in different states and their different sensitivities to messages. In our framework, we take user engagement and system impact as two sides, directly indicating the potential risks and their sources, which is not available in previous studies.

Basic statistics of the model results show that the mean of participation increases from state 1 to 2 to 3, and the variance declines accordingly. Following the concept of "Human-Tech Dominance", we label the relationship in state 1 as "User-dominated". Users in this relationship generally are not equipped with high participation (low mean), but the freedom of participation is high (high variance), indicating an unstable status. It can be inferred that user behavior in this state are mainly affected by their own characteristics rather than platform strategies. Similarly, in state 2, we label the relationship as "Balanced", which means that the user engagement and freedom in this relationship are moderate (mean and variance are moderate). For users in this state, while the platform could influence their decisions through certain means, they present autonomy to some extent. In State 3, we name the relationship as "System-dominated". Showing a kind of "concentrated investment" (Zhang et al., 2019), users in this state are greatly affected by platform strategies.

As for state transitions, the “Balanced” users represent a high average retention bias (69% and 74% respectively). Additionally, users at "System-dominated" state tend to have a significant transition to a "User-dominated" state (65% and 61% respectively), which highlights the instability of the former relationship.

As for parameter estimation of reminders, when the state evolves from 1 to 2 to 3, the linear effects of *Reminder* remains positive and significant while the effect of *Reminder* on the opposite direction are not. That is to say, the reminder message can promote users' participation by promoting the development of customer relationship from user-dominated to system-dominated. *Num_reminder* has nonlinear (inverted U-shaped) impacts on participation, but this impact differs among various states: users of User-dominated state are obviously more difficult to get bored, while users of System-dominated state start to resist the intrusion of such information much earlier. It means that the more the customer relationship is dominated by the system, the earlier the inflection point of nonlinear influence of cumulative reminder messages occurs.

6. Conclusion and Implications

In this study, we mainly investigate the effect of reminder messages as a new CRM method on customers’ participation. Additionally, moderating effects and the underlying mechanisms are also explored in our research. The analysis results suggest that the reminder message has positive effects on customer participation, while "technostress" causes the inverted U-shaped effect of the reminder frequency. On average, when the number of reminder messages received by a user exceeded 5.25, the user’s

[3] https://github.com/MrElbow123/hmm_in_crm

probability of entering the live stream decreased with the increase of reminder messages. In addition, compared with working hours, the reminder message has a greater impact on participation when the corresponding live streaming is during after-work hours. The impact of reminder message wears off as the customer's usage level of the live streaming platform increases.

Further, reminder messages show different effects depending on the relationship status of users. We introduce the concept of "Human-Tech Dominance" to explain this phenomenon. Specifically, the continuous promotion of reminder messages can indeed promote the relationship between users and the platform to a deeper stage, manifesting a positive effect. However, in terms of the state itself, the more the customer relationship is dominated by the system, the earlier users will perceive the technostress, and the stronger the non-linear influence of cumulative reminders will be.

Our paper is among the first to explore the influence mechanism of "reminder messages" on academic live streaming platforms. Referring to previous studies, we use an HMM model to capture the dynamics of customer relationships. Our study enriches the results of previous studies about email and short message service where a similar inverted U-shaped effect was found (Hao, 2019; Zhang et al., 2017). Moreover, our study creatively introduces the concept of "Human-Tech Dominance" into the analysis of customer relationships. Compared with the traditional user engagement stage theory, this concept of emphasis on dominant relationship can better explain the heterogeneity of users and their different sensitivity to reminder messages in different states.

Our results in this paper have a number of useful practical implications. Firstly, platforms can send reminder messages to motivate customer participation. However, they should pay some attention to the heterogeneity of users, given that uniform standards will only bring unnecessary losses. Our research shows that various factors such as the time of live streaming and user usage level will impact the effect of the reminder messages. Instead of adhering to some fixed frequency metric, companies should dynamically adjust their message strategies considering these factors. Second, based on "Human-Tech Dominance", keeping users in the balanced state could be a better choice for companies. The statistical results indicates the high stability and low volatility of user behavior in this state. When the user is in a user-dominated state, the platform needs to provide appropriate reminders as guidance. When the user is in a state of balance, the platform needs to reduce the frequency of reminders to prevent the user from entering system-dominated state.

Before concluding, it is worth discussing some limitations of our study. Limited by data resources and experimental scenarios, we did not consider the heterogeneity of reminder messages' content. However, we believe that this heterogeneity is still worth paying attention to, and future research can compare the effects of different contents of reminder messages, so as to find a more comprehensive model of customer relationship management through reminder messages.

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