First Service Communication Media and Subsequent Patient Engagement: Evidence from a Mobile Mental Healthcare Platform

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Abstract

Sustaining user engagement is a major challenge for mobile platforms, particularly in telehealth. Patients’ initial interactions with healthcare providers may affect their subsequent engagement. Yet, little is understood on the role of interactive media in the first service. This study investigates the rich media communication in the first service and its effect on subsequent patient engagement. Using data from a leading Chinese mobile mental healthcare platform, we find that rich media usage leads patients to more subsequent participation, measured by service retention, frequency, and payment in the following month. The results are statistically significant and consistent across different identification strategies, including matching and instrumental variable analysis. In addition, the effect is mainly driven by patients with mild mental conditions, instead of severe ones. Last, we evaluate alternative personalization strategies and find targeting patients with predicted high retention lift scores is most effective to sustain user engagement.

Keywords: Mobile Platform, Media Richness, Engagement, Mental Health, Machine Learning

1. Introduction

A major challenge confronted by many digital platforms is the majority of their users only consume once and then become inactive without subsequent engagement. An online report given by Zaius in 2020 demonstrates that three-quarters of first-time purchasers do not make a second purchase from the same eCommerce platform. As for the healthcare service, a recent article in 2020 found US healthcare systems are experiencing a churn rate of 48%. In practice, although most platforms have made substantial investments (e.g., informative and persuasive adverts, monetary incentives, social cues) in attracting consumers to engage in their products and services, many users do not bring further profit after their first consumption. In most cases, platforms have only one chance to attract users to stay, and it is thus crucial for platforms to improve their first service offering.

Information Systems (IS) literature has studied user repurchase behavior in a variety of contexts, such as advertising (Li et al. 2019), retailing (Ulku et al. 2020), insurance (Cheng et al. 2021). However, few studies investigate communication modes of first service and their impacts on subsequent consumption, especially in mental health contexts. A stream of research has explored the role of information presentation media of products in the retailing context (Jiang and Benbasat 2007), the findings may not readily be applied to mobile healthcare services due to the differences between patients and ordinary consumers. Two types of user attributes can be considered in the mental healthcare setting when designing engagement strategies: users’ health status and their service usage pattern. First, patients suffering from mental illness with different severity may be disproportionately affected by different interactive communication media (i.e., text, image, audio,
video). Second, patients with different service usage behaviors may also bring heterogeneity in the effectiveness of communication strategies. Marketing research has begun exploring effective personalization strategies to sustain service engagement (e.g., Ascarza 2018; Lemmens and Gupta 2020). Generally, three main strategies have been discussed: (i) targeting consumers with the highest churning probability (RISK model), (ii) targeting those with the highest increment of retention probability after interventions (LIFT model), and (iii) targeting those with the highest increment of profit after interventions (PROFIT model). Yet, little understanding is on the relative effectiveness of these targeting strategies for patient engagement on a mobile health platform.

Integrating the above research gaps, we ask the following three research questions: (1) Does rich media usage of the first service communication affect patient participation in subsequent mental healthcare? (2) If so, does the effect depend on the severity of mental health conditions? and (3) Which targeting strategy is more effective when motivating the usage of rich media channels?

2. Related literature
This work builds on the literature on mobile health technology, media richness of online services, user repurchase, and target strategy for user retention. First, this study is related to health IT and medical research on mobile health (mHealth) information technology (e.g., Kumar et al. 2018). Research has shown the potential of using mobile apps and SMS text messaging as interventions to mitigate health problems (e.g., Ghose et al. 2021). Some studies also offer empirical exploration on mHealth for mental health issues and call for effective app design to tailor to such patients (Anthes 2016; Beard et al. 2019). To respond to the call, we study mental healthcare platforms and examine patients’ subsequent engagement after their first mobile health service communication.

Second, this study builds on the literature on the information/media richness of online services (e.g., Dennis et al. 2008). This stream of work has a consensus: higher media richness is more effective to facilitate decision-making since rich media (e.g., audio or video) conveys more interactive information than lean media (e.g., text or image). Moreover, Tseng and Wei (2020) show mobile ads with high media richness have a high impact on early-stage consumer behaviors (i.e., attention, interest, search) while a low impact on the later stages (i.e., action, share). To extend this line of research, we shift the research focus from conventional online services to healthcare.

Third, this study is relevant to the IS literature on user repurchase. This literature has documented that satisfaction and loyalty are the main drivers of user repurchase intention in online retailing (Fang et al. 2014; Liu-Thompkins and Tam 2013). Our study focuses on consumers with mental health issues. The behaviors of mental illness patients are different from those of ordinary consumers. In general, the consumption experiences and outcomes are equally meaningful for ordinary consumers, but patients may care much more about the diagnosis outcomes than the service process, and for this context, the impact of rich media usage is not clear in the literature.

Last, this study is related to a nascent stream of marketing research on effective targeting strategies for customer retention. In practice, firms across various sectors (e.g., telecom, pay-TV, credit cards) detect customers at the high risk of churning and target retention efforts to them. This strategy allows firms to allocate their effort to the customers who are truly at risk of churning rather than wasting resources on those who would have stayed regardless. However, Ascarza (2018) proposes a response-based strategy—a way to target the consumers who have the highest increment of
retention after the intervention—and demonstrates that this lift strategy is superior to the conventional risk strategy. Following up on this work, Lemmens and Gupta (2020) propose a profit-based consumer targeting algorithm and stress the superiority of profit lift over retention lift. While these marketing studies advocate response- and profit-based targeting strategies, it is still unclear which one works better in the context of personalizing mobile mental healthcare.

3. Context and Data

To empirically examine the research questions, we use a unique dataset from a leading Chinese mobile mental healthcare platform. By cooperating with physicians, this platform provides a variety of services, including online consultation, diagnosis, prescription, and drug consumption, to patients. The registered physicians can invite their patients to join this virtual platform and instruct them how to use this app. Several interactive media are available on this platform, including the video (i.e., an online meeting), audio (i.e., a phone call), and text with images, and physicians can choose which ones to make available for patients. After ordering services on this platform, a patient can synchronously interact with her/his physicians through only one medium during service time. Our dataset comprises 21,265 patient-level observations spanning six years from 2015 to 2020. Each patient corresponds to an observation that contains information about their characteristics, their physician’s characteristics, first service medium, and their purchases in subsequent one month (i.e., the period from the first service to the same day of the next month).

Following advertising literature (e.g., Rosenkranz 2009), we classify media into rich media (that can display sensory traits, such as video, audio, or animation) and lean media (text and image). Hence, we construct a dummy independent variable, \( RM_i = 1 \) if the first service of the \( i \)th patient is only processed via audio or video, \( =0 \) if the first service is only processed by text and image). Referring to the work of Lemmens and Gupta (2020), we set the first dependent variable \( Retention_i \) to 1 if the \( i \)th patient returns to order services (i.e., at least one service) on the app in 1 month after the first service, otherwise to 0 if she/he has churned (i.e., no service). Another two dependent variables are \# Service in 1 month\(_i\) and \$ Service in 1 month\(_i\), which indicate the number of services and total payment of the \( i \)th patient, respectively, in the following 1 month after the first service.

To account for observed confounders, we include a vector of covariates (\( X_i \)) about patients, corresponding physicians, first service year, and month. For patients, we concern their payment in the first service, their basic characteristic (i.e., age, gender, city), and their health conditions (i.e., whether have depression, anxiety, bipolar disorder, and schizophrenia). For physicians, we control their gender, age, title, hospital, and city. All covariates, except age, are dummy variables.

4. Methods

4.1. Effects of Rich media Usage
Ordinary Least Squares (OLS). We first use OLS estimate to examine the association between the first services communication modes and patients’ subsequent purchase behavior:

\[
Y_i = C_0 + \beta_1 RM_i + X_i' B_0 + \varepsilon_i,
\]

where \( Y_i \) indicates retention (0-1), number of services (#), and total payment ($) in a month after the first service, \( X_i \) is the set of covariates, and \( \varepsilon_i \) is an error term. The year and month dummies for each patient’s first service are included to account for mobile app design changes over time.
Propensity Score Matching (PSM). The OLS estimator may be biased if there exists overt self-selection by patients. Accordingly, we adopt PSM to mitigate this concern. In essence, this approach attempts to remove the observed selection bias by generating balanced covariate-specific treatment (=1 if rich media usage)-control groups (=0 if lean media usage).

Instrumental Variable (IV) Analysis. To further account for unobservable confounders, we employ an IV analysis. The IV here is the percentage of rich media usage by the same physician with other patients (rather than with the \(i\)th patient) before the focal service. As physicians instruct their patients to use the app for the first time and each of their medium preferences may be fixed over time, the medium used by a physician’s \(i\)th patient could align with that of this same physician’s other patients. Thus, the \(IV_i\) is strongly correlated the independent variable (i.e., the choice of communication medium with the \(i\)th patient), but does not directly affect dependent variables (i.e., the subsequent purchase behaviors of the \(i\)th patient) as the physician’s other patients’ behaviors are exogenous to the subsequent behaviors of the focal patient. This IV is referred to as a “leave-one-out” IV, which has widely been used in IS literature (e.g., Belo et al. 2014; Bavafa et al. 2018).

4.2. Effect Heterogeneity across Mental Disease Severity

Next, we test the heterogeneous effects of rich media usage across severity (i.e., mild vs severe) of mental illness. First, we categorize patients into four subgroups, each with a specific type of mental disease, including depression, anxiety, bipolar disorder, and schizophrenia, respectively. We replicate the baseline OLS estimation (Eq. 1) for each subsample, and then we compare and contrast these estimates to examine the treatment effect heterogeneity of rich media usage.

4.3. Effect Heterogeneity across Targeting Strategies (Churn Risk, Retention Lift, Profit Lift)

Last, when applying a patient-engagement intervention that incentivizes patients to use rich media in the first service, it is crucial for platforms to identify and select the suitable customers to target for the best performance. We study the effectiveness of targeting strategies based on the probability of churning (RISK model), increment of retention lift (LIFT model), and increment of profit lift (PROFIT model) after using rich media channels. Considering the \(i\)th patient with attributes \(X_i\) (e.g., past behavior, demographics), and let \(RM_i\) denotes the used rich media usage (=1 if used, otherwise =0). \(Churn_i\) refers to no service for the \(i\)th patient in one month after the first service.

\[
Risk_i = P[Churn_i = 1|X_i, RM_i = 0] \\
Lift_i = P[Retention_i = 1|X_i, RM_i = 1] - P[Retention_i = 1|X_i, RM_i = 0] \\
Profit_i = E[Profit_i|X_i, RM_i = 1] - E[Profit_i|X_i, RM_i = 0]
\]

We use machine learning (ML) techniques to predict and measure the three variables for each customer. We compare various algorithms (e.g., logistic regression, random forest, support vector machine) and select Random Forest for the prediction due to its greatest out-of-sample predictive performance. It is notable that when predicting retention lift and profit lift scores, we need to compare patient behaviors in reality and counterfactual that cannot both be observed. A randomized experiment is ideal to estimate the average treatment effect in a counterfactual setting. As such an experiment is not available in our context, we follow Lemmens and Gupta (2020) and apply the PSM in the 50% training sample to simulate the randomized experiment results. The predicted differences in the retention rates and profits in the next month between the treatment and control groups are the retention lift and profit lift scores for each patient, respectively.
The effect of rich media usage is evaluated in different groups of patients, depending on their predicted scores of RISK, LIFT, and PROFIT models. More specifically, first, we rank the users based on the three scores and segment them into deciles (i.e., 0-10%, 10%-20%, ..., 90%-100%) using each method, respectively. Second, we select the top P (e.g., 30%) of patients as the “targeted subgroup” and replicate the OLS estimates (Eq. 1) to obtain the effects of rich media usage for all “targeted subgroups”. As seen, when the top P increases, the number of patients in each group increases, with P=100% corresponding to targeting the whole patient base. In doing so, the magnitude of the treatment effects on patients in the top deciles of risk, lift, and profit scores can be compared in order to assess the relative performance of these three personalization strategies.

5. Results

Table 1 presents the results on the effects of rich media usage. We find that patients who use a rich medium in their first service are statistically significantly associate with an increase in the retention probability ($\beta = 0.091$, $p<0.01$), service frequency ($\beta = 0.113$, $p<0.01$), and payment ($\beta = 0.636$, $p<0.001$) in the following month, compared to patients who use a lean medium to interact with physicians. The observed effect is consistent in PSM and 2SLS. These findings indicate that using rich media in the first service leads patients to sustain their engagement, which is observed as higher retention, more services, and larger payment of purchases in the subsequent month.

### Table 1. Relative Effects of Communication Channels (Rich media Vs. Lean Media) on Subsequent Retention, Service Frequency, and Payment in the Following Month

<table>
<thead>
<tr>
<th></th>
<th>DV: Retention (0-1 service in 1 month)</th>
<th>DV: Frequency log (# Service in 1 month + 1)</th>
<th>DV: Payment log ($ Total in 1 month + 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.091***</td>
<td>0.113***</td>
<td>0.636***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.013)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>PSM</td>
<td>0.109***</td>
<td>0.130***</td>
<td>0.732***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>IV-2SLS</td>
<td>0.090*</td>
<td>0.165***</td>
<td>0.732**</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.056)</td>
<td>(0.326)</td>
</tr>
</tbody>
</table>

Note: All covariates in Table 1 are omitted here for brevity. First stage F statistics are 409.54, 510.37, and 332.11 for the IV analyses. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 1 presents OLS estimates with 95% CI for four subsamples with distinct mental diseases. The three panels from left to right show estimates for treatment effects on the retention, service frequency, and payment respectively. Estimates are positive and significant for three mild mental diseases, but not statistically significant for schizophrenia, a severe mental illness.
Figure 2 presents and compares the treatment effects on subsequent engagement, frequency, and total payments in the next month on all top P subgroups (e.g., top 30% meaning top 3 deciles of risk, lift, and profit scores). It is done by replicating OLS estimates (Eq. 1) on the subgroups using the three strategies (§4.3). For the engagement (the left panel), from the top 10% to 30%, the effects for retention lift subgroups (in red) are much larger than those for churn risk (in blue) and profit lift (in green) subgroups. From the top 40% to 80%, effects for profit lift subgroups are slightly larger than the retention lift ones but still substantially larger than the churn risk ones. Such results apply to all dependent variables and imply that: when the number of patients to recommend rich media communication is limited, targeting those with high retention lift scores achieves the best performance in sustaining user engagement, being the most effective strategy.

6. Discussion and Conclusion

In this study, we examine the relative effects of the rich media (versus lean media) usage in the first mental health service of patients on their subsequent engagement in mental healthcare. Using data from a leading Chinese mobile mental health platform, we find that the use of rich media channels in the first service is associated with better repurchase performance, measured by retention, service frequency, and payment in the following month. Moreover, we find that such an effect is substantial for mental health patients with mild conditions (e.g., depression), compared to those with more severe conditions (i.e., schizophrenia). Last, we compare personalization strategies to tailor rich media communication to patients. We find that targeting patients with a predicted high retention lift works the best to increase their subsequent engagement.

This study has the potential to make important contributions. First, motivated by the challenge of low repurchase rate on mobile platforms, this study initiates the empirical effort to associate the rich media communication in the first service with patient repurchase behaviors in mobile mental healthcare platforms. Second, this study demonstrates the potential of rich media channels in sustaining user engagement, offering important design and business implications for mobile platforms. Third, the results that the rich media effect is contingent on the disease severity suggest a viable patient segmentation strategy for mHealth platforms. Last, our results support that targeting patients with high retention lift scores after the use of rich media in the first service is the most effective personalization strategy to sustain user engagement on mHealth platforms.

(References are available upon request but are omitted due to the space limit)