Promoting Mobile Health Adoption to Hospital Patients Through Social Influencers: A Multi-Group Analysis Among Patients With High vs. Low Hospital Usage

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ABSTRACT

Mobile health (mHealth) plays a key role in improving healthcare interventions by engaging patients in healthcare management. Still, there is a paucity of empirical studies on the extent to which mHealth adoption could be effectively promoted via social influencers (clinicians, caretakers, or other patients) who have shown to significantly influence health-related behaviors of patients. A multi-group analysis of 253 hospital patients revealed that while social influencers have a strong influence on mHealth adoption, the effect only exists among patients who have high hospital usage. Even so, the positive relationship between technology-related factors including perceived quality of mHealth interventions and opinions on mHealth, patients' personal motivation to adoption, and patients' adoption intention are not affected by their hospital usage frequency. Insights on forward-looking recommendations and practical implications on mHealth promotion are highlighted.

KEYWORDS

Digital Health Intervention, Health Communication, Hospital Mobile Apps, mHealth, Mobile Health

1. INTRODUCTION

Mobile health (mHealth) technology is inevitably vital in transforming healthcare delivery nowadays vis-à-vis the co-creation of treatment experience and empowerment of patient self-management in the continuum of care (Free et al., 2013). In fact, mHealth has been touted as an essential facilitator to the achievement of United Nations' (UN) sustainable development goal (SDG) #3: "Ensure healthy lives and promote well-being for all at all ages" (ITU, 2017; UN, 2015).

Since 2016, companies and health organizations have provided 259,000 health apps in app stores in which 65% has targeted chronically-ill patients (Research2Guidance, 2016). By 2026, the global mHealth consumer market is forecasted to reach \$206.1 billion, representing a growth of 31.6% CAGR from 2020 (ReportLinker, 2020). While the consumer mHealth market records significant growth

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in apps provision, public health providers also seek to accelerate mHealth adoption among hospital patients to reduce healthcare cost while enhancing the quality of patient care (Jacob, Sanchez-Vazquez, & Ivory, 2020). Amidst the recent COVID-19, governments and hospitals across the globe have advocated the role and importance of mHealth in the monitoring and management of the pandemic (Ming et al., 2020; Singh, Couch, & Yap, 2020). Additionally, for patients with chronic illnesses who are in quarantine with social-physical distancing restrictions, mHealth provides a good platform for healthcare delivery (Torous & Keshavan, 2020). Yet, the low mHealth adoption rate has posed a grand challenge to policymakers, healthcare technologists and clinicians (Jacob et al., 2020; Ye et al., 2019).

To date, mHealth studies have focused primarily on the mHealth adoption from information communication technologies (ICTs) or health informatics perspectives whereas social influence on its adoption has largely been neglected (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016). In prior mHealth studies, personal and social motivations have simply been examined as one of the antecedents of mHealth adoption along with technology-related factors (Davis, Bagozzi, & Warshaw, 1989; Jacob et al., 2020; Sun, Wang, Guo, & Peng, 2013; Venkatesh, Morris, Davis, & Davis, 2003). Nonetheless, since people react in different ways under social influence from others around them (Griffin, Grace, & O’Cass, 2014), it is crucial to understand the interplay between patients’ characteristics and social motivation for policymakers to enhance the promotional effectiveness of mHealth adoption (Lupton, 2014). Accordingly, this study intends to bridge this noteworthy research gap by exploring the impact of social influence on mHealth adoption among hospital patients with the two primary research objectives posited herein:

1. To explore the impact of patients’ usage frequency of hospital services on personal and social motivations to mHealth adoption;
2. To collect quantitative data to assess (i) the impact of patients’ hospital usage behavior on their motivation to adopt mHealth and (ii) the relative importance of social influencers, namely clinicians, caretakers, and other patients, on mHealth adoption.

Apparently, while demographics of patients has been shown to moderate motivation-adoption relationship (Francis, 2019; Zhao, Ni, & Zhou, 2018), hospital policymakers will typically find it difficult, if not impossible, to promote mHealth interventions to patients segmented by demographical characteristics. Conversely, it is more feasible to implement advertising and promotion plan vis-à-vis the patients’ behavioral characteristics (Davis, Jacklin, Sevdalis, & Vincent, 2007). Hence, audience segmentation based on patients’ behavioral characteristics such as usage frequency of hospital services is an emerging field of interest with limited evidence as advanced by objective (1) of this study.

As well, amidst social influencers, healthcare professionals and clinicians are known to have proven effect on health-related decisions of patients even though prior studies scarcely explored the relative importance of various social influencers (clinicians, caretakers, and other patients) on mHealth adoption (Dwivedi et al., 2016; Jacob et al., 2020; O’Connor et al., 2016). Hence, this knowledge gap will be addressed by objective (2) of this study, investigating the relative importance of social influencers. Results of this study will help hospital policymakers to formulate effective mHealth promotion strategies and contribute to the research gap in the interplay between social motivation and patients’ behavioral characteristics.

Briefly, the organization of this paper is as follows. Following the introduction, Section 2 overviews the conceptual background for the study and hypotheses whereas Section 3 details the study methodology, highlighting the research sampling and measurement issues. Section 4 then shifts focus to results and findings, reflecting on the data analysis to fill the research gaps in social influence and mHealth adoption among hospital patients. In Section 5, the paper closes with insights into study limitations and future research directions.

2. BACKGROUND AND HYPOTHESES

A systematic review of the extant literature has identified four overarching themes affecting mHealth adoption of patients seeking for self-empowerment, engagement and personal involvement in their health management (Chauhan, Chauhan, Jaiswal, & Jaiswal, 2017; Fiordelli, Diviani, & Schulz, 2013; Jacob et al., 2020; Muller, Alley, Schoeppe, & Vandelanotte, 2016; O'Connor et al., 2016; Sun et al., 2013; Zapata, Fernández-Alemán, Idri, & Toval, 2015). As detailed below, factors affecting mHealth adoption are categorized into four key areas: (1) quality of mHealth interventions; (2) opinion on mHealth; (3) personal motivation; and (4) social influence.

Based on the four dimensions of mHealth adoption, a theoretical framework is conceptualized in Figure 1, which illustrates the impact of perceived mHealth quality, patients' opinion on mHealth usage effort, patients' intrinsic motivation, and influence from social influencers on mHealth adoption. First, the framework is used to confirm the four dimensions of factors affecting mHealth adoption among hospital patients as posited by extant research. Second, it is used to assess the impact of the four dimensions of factor on the adoption of mHealth among patient groups with high v. low hospital usage behavior as hypothesized below.

2.1 Quality of mHealth Interventions

Quality of mHealth interventions refers to the perceived quality of health information and interventions patients received via ICTs such as mobile phone and other internet-connected mobile devices (O'Connor et al., 2016). The perceived quality of mHealth interventions has shown to be affected by technology-related factors from technology acceptance theories, for example, the task-technology fit theory (TTF), the innovation diffusion theory (IDT), the technology acceptance models (TAM), and the unified theory of technology acceptance and use of technology (UTAUT) (Davis et al., 1989; Duarte & Pinho, 2019; Venkatesh et al., 2003).

As mHealth adoption encompasses technology use, empirical studies have exemplified that technology-related factors are significantly related to patients' motivation to mHealth adoption. Hence, this study proposes to confirm the below relationship prior to the testing of other factors in the hypothesized model:

H1: Perceived quality of mHealth interventions will be positively related to the patients' motivation to adoption.

2.2 Opinion on mHealth

Opinion on mHealth refers to the patients' opinion on technology use effort for health interventions (O'Connor et al., 2016).

Patients who are familiar with use of ICTs such as smartphones will surely have the knowledge and skills to use mHealth technologies or have resources to facilitate the use of mHealth interventions and will be more motivated to adopt mHealth (Davis et al., 1989; Jacob et al., 2020; Venkatesh, Thong, & Xu, 2012). This study seeks to confirm the relationship between patients' opinion on mHealth vis-à-vis their individual motivation to adopt mHealth.

H2: Opinion on mHealth will be positively related to the patient's motivation to adoption.

2.3 Personal Motivation

Personal motivation of patients to be engaged acts as an important factor to affect the results of healthcare interventions vis-à-vis the adoption of mHealth interventions (Hird, Ghosh, & Kitano, 2016; O'Connor et al., 2016; Ye et al., 2019).

Hence, patients who are motivated to engage in their healthcare interventions will be more willing to self-manage their health-related behaviors using mHealth technologies. Thus, we postulate the below to verify the motivation-adoption relationship:

H3: Patients' personal motivation will be positively related to the intention to adopt mHealth.

2.4 Social Influence

Social influence relates to social motivation that affects the patients' motivation and intention to adoption (O'Connor et al., 2016).

The elements of social motivation can range from advertising and promotion, recommendations from clinicians or trusted health organizations, to recommendations from significant others to the patients, and/or word-of-mouth recommendations from other patients (Ajzen, 1991; Martin, 2017; Venkatesh et al., 2003). As such, this study also proposes to validate the effect of social influence on patients' personal motivation and mHealth adoption intention:

H4a: Social influence will positively affect the patients' personal motivation to adoption.

H4b: Social influence will positively affect the patients' adoption intention of mHealth.

While clinicians have shown to exert a strong influence on patients' health-related decisions (Kelley, Kraft-Todd, Schapira, Kossowsky, & Riess, 2014), little research attention has been given to explore the importance of the clinicians' endorsement as compared to other social influencers affecting a patient's mHealth adoption. Thus, this study postulates to assess the relative importance of clinicians among social influencers on the patient's adoption intention.

H5a: Influence of clinicians will be relatively stronger than the influence of patients' family members and friends on the patients' adoption intention.

H5b: Influence of clinicians will be relatively stronger than the influence of other patients on the patients' adoption intention.

2.5 Behavioral Characteristics of Patients and mHealth Adoption

Griffin et al. (2014) argued that people react to health marketing communications in different ways under social influence while individuals' characteristics are key determinants. Previous studies have also identified that demographics of patients including age, gender, education level, ethnicity, and socio-economic status can affect the relationship between antecedents and the adoption of mHealth (O'Connor et al., 2016). Yet, it is impractical to promote mHealth in hospitals using demographic segmentation, for example, despite the fact that younger and more educated patients will tend to be more digital savvy, resulting in a higher adoption intention (Venkatesh et al., 2012), age and education-level segmentation for mHealth communication in hospital is infeasible due to segment accessibility issue (Slater, 1996).

To date, there has been increasing mHealth research attention on the behavioral characteristics of patients such as type of illness and/or treatment plan (Castro Sweet et al., 2017; Free et al., 2013; O'Connor et al., 2016). Although the audience segmentation that is based on behavioral characteristics has been well documented in earlier patient involvement and engagement studies (Davis et al., 2007), mHealth research rarely study the impact of patients' behavioral characteristics other than type of illness and/or treatment plan. While some studies suggested that patients with less severe conditions that require less hospital usage may be more proactive in managing their health care, other studies suggested otherwise (Flynn, Gregory, Makki, & Gabbay, 2009; Hopp, Hogan, Woodbridge, & Lowery, 2007).

Figure 1. Theoretical Framework

Accordingly, this study postulates to examine the impact of the patients' usage frequency of hospital services on the relationship between their motivation and intention to adoption.

- H6a:** Relationship between patients' personal motivation and mHealth adoption will be stronger among patients with higher hospital usage.
- H6b:** Relationship between social influence and personal motivation will be stronger among patients with higher hospital usage.
- H6c:** Relationship between social influence and mHealth adoption will be stronger among patients with higher hospital usage.

3. METHODOLOGY

3.1 Sampling and Data Collection

The study sample encompasses a cross-sectional survey of hospital patients that have smartphones with experience in using mobile apps. Patients who are non-smartphone users would have no prior references to comment on the perceived quality of health interventions currently provided free-of-charge by public hospitals in Hong Kong.

The self-administrated questionnaire was distributed at the pharmacy of a public hospital in Hong Kong by hospital volunteers. Patients, who were waiting for drug dispensing, were invited to complete a paper questionnaire. Targeted respondents were identified by hospital volunteers via a screening question to screen out non-smartphone users. Of 263 questionnaires collected, 253 usable responses were obtained.

Table 1 summarized the demographic profile of the study respondents.

Table 1. Demographic Profile of Respondents

		Low hospital usage group	High hospital usage group
Total no. of respondents		143	110
Age		100%	100%
	<20	6%	6%
	20-34	35%	23%
	35-49	33%	39%
	50-64	23%	25%
	>=65	3%	7%
Gender		100%	100%
	Male	43%	35%
	Female	57%	65%
Experience in hospital apps			
	% of respondents aware of apps provided by the hospital	36%	45%
	% of respondents had hospital apps installed	7%	12%

3.2 Instrumentation

The quality of mHealth interventions and opinion on mHealth were measured using factors adopted from the prominent technology acceptance model (TAM), which includes perceived usefulness and perceived ease of use of mHealth technologies, as these factors have proved to explain the perceived quality and opinion with respect to the adoption of mHealth (Gagnon, Ngangue, Payne-Gagnon, & Desmartis, 2015). Other measures used in this study include patients' personal motivation, social influence and intention to adopt mHealth, as adopted from Fisher, Fisher, and Harman (2003) and Taylor and Todd (1995). All scales were reflectively measured by validated measurement items using a five-point Likert scale (1 = strongly disagree v. 5 = strongly agree).

Table 2 summarized the items and scales used in the questionnaires.

To facilitate the feasibility of implementing mHealth communications in the hospital setting, hospital usage frequency was measured as a categorical variable as per the usage number of hospital services within six months prior to the survey (Agresti & Kateri, 2011). Patients were categorized as high usage group when they have used hospital services for four times or more in the last six months v. low usage group for using less than four times.

In our study sample, 110 respondents (43%) fell into the high usage group v. 143 respondents (57%) characterized as having only low hospital usage.

3.3 Data Analysis

On examining the hypothesized interactions between patients' hospital usage frequency and their motivation to adoption, a partial least squares structural equation modeling (PLS-SEM), multi-group analysis (MGA), as well as the importance-performance map analysis (IPMA) were conducted via SmartPLS 3.0 (Ringle, Wende, & Becker, 2015).

Table 2. Measurement Model

Scale and items		Loadings	AVE	Composite reliability	Cronbach's alpha
Quality of mHealth			0.919	0.972	0.956
	Mobile health makes using hospital service easier	0.955			
	Mobile health makes using hospital service convenient	0.960			
	Mobile health is useful to me	0.961			
Opinion on mHealth			0.822	0.933	0.891
	My interaction with mobile health is clear & understandable	0.933			
	Mobile health will be easy to use	0.925			
	It is easy for me to become skilful at using mobile health	0.860			
Patients' Personal Motivation			0.713	0.881	0.795
	I am interested in using mobile health	0.762			
	I think mobile health is more satisfying than existing ways of using hospital service	0.903			
	I think mobile health is more satisfying than existing ways of acquiring hospital information	0.861			
Social Influence			0.752	0.901	0.836
	My family members and friends think that I should use mobile health	0.875			
	Health care professionals think that I should use mobile health	0.894			
	Other patients think that I should use mobile health	0.831			
Adoption Intention of mHealth			0.890	0.942	0.877
	I intend to use mobile health	0.946			
	I predict I will keep using mobile health	0.941			

PLS-SEM does not require normality condition as a prerequisite, enable the examination of stability of estimates and interaction effects via bootstrap resampling, and is widely adopted in marketing research (Hair, Hult, Ringle, & Sarstedt, 2016; Henseler, Ringle, & Sinkovics, 2009). The conceptual model in this study was examined via PLS-SEM with SmartPLS 3.0 statistical software (Ringle et al., 2015). Model estimation via PLS-SEM will deliver “empirical measures of the relationships between the indicators and the constructs (measurement models), as well as between the constructs (structural model)” (Hair et al., 2016, p. 105).

As all the latent variables in the theoretical framework were reflectively measured, the internal consistency, convergent, and discriminant validity of the latent variables in the measurement model were examined following the guidelines recommended by Anderson and Gerbing (1988). The following reliability and validity measures will be assessed (Fornell & Larcker, 1981):

1. Composite reliability > 0.7 , indicating internal consistency reliability;
2. Factor loadings are significant ($p < 0.01$) and average variance extracted (AVE) > 0.5 , establishing scales convergent validity; and
3. The square root of AVE for each construct should be greater than the correlations between pairs of latent variables, supporting discriminant validity.

After the reliability-validity measures of the measurement model have been assessed, the relationship between the dependent and independent variables in the structural model will be assessed vis-à-vis the following guidelines (Cohen, 1998; Hair et al., 2016, pp. 208-209):

1. VIF of each set of predictors > 0.2 and < 5 , showing the structural model is absent of collinearity problems;
2. Bootstrapping with 5000 bootstrap samples and target to have significance of path coefficients β ($p < 0.05$), showing a significant relationship between latent variables;
3. Variance explained $R^2 > 0.25$, indicating the structural model's predictive power;
4. Effect size $f^2 < 0.15$, indicating small to medium effects of an exogenous construct on an endogenous construct;
5. Predictive relevance $Q^2 > 0$, suggesting exogenous constructs have predictive relevance for the endogenous construct;
6. Effect size $q^2 < 0.15$, indicating small to medium predictive relevance of an exogenous construct for the endogenous construct; and
7. Standardized root mean square residual (SRMR) < 0.08 , indicating good model fit for the hypothesised model.

4. RESULTS AND FINDINGS

After the two-step process to assess the measurement and structural models separately, the PLS analysis was performed prior to the advanced PLS-MGA and IPMA analysis (Chin, 1998; Hair et al., 2016).

These analytic procedures were performed to answer the two research objectives presented:

1. To explore the impact of patients' usage frequency of hospital services on personal and social motivation to mHealth adoption; and
2. To examine the relative importance of social influencers (clinicians, family and friends, or other patients).

4.1 Measurement Model

All latent variables were measured reflectively so the measurement model is evaluated following non-parametric quality criteria (Chin, 2010).

As shown in Table 2 and Table 3, all data met the criteria of assessing the convergent validity, internal consistency, reliability, convergent and discriminant validity of measurement scale (Chin, 1998; Fornell & Larcker, 1981):

- Loadings of all indicators should be greater than 0.7;

Table 3. Discriminant Validity

Construct	Mean	SD	Quality	Opinion	Personal motivation	Social influence	Adoption intention
Quality of mHealth	4.10	0.89	0.959				
Opinion on mHealth	4.22	0.92	0.443	0.907			
Personal motivation	4.00	0.87	0.778	0.515	0.844		
Social influence	3.87	0.99	0.624	0.493	0.624	0.867	
Adoption intention	3.88	1.05	0.519	0.382	0.627	0.525	0.944

- Composite reliability should exceed 0.7;
- AVE of each construct should be greater than 0.5 and exceed the highest squared correlation with any other constructs; and
- Cronbach's alpha of each construct should be greater than 0.7. Upon the confirmation that the construct measures are reliable and valid, the structural model will be assessed subsequently.

4.2 Structural Model

Bootstrapping with 5000 re-samples was conducted to evaluate the structural model so as to confirm the degree of statistical significance of the hypothesized model according to the criteria proposed by Hair et al. (2016, pp. 208-209).

The R^2 of all dependent variables exceeded the threshold value of 0.2 showing strong predictive power of the model (R^2 of personal motivation = 0.698 and R^2 of adoption intention = 0.449). Overall, the model explained 69.8 percent of the variance in patient's personal motivation and 44.9 percent of the variance in intention to adopt mHealth. VIF were less than 5, indicating the absence of multicollinearity problem. All effect size f^2 exceeded 0.02, which indicated that all exogenous construct has medium to large effect on endogenous constructs. All Q^2 values were larger than zero suggesting predictive relevance. SRMR value was less than 0.8 indicating good model fit.

With all the key criteria for evaluating structural model met, the main effects hypotheses, MGA and IMPA of the research model will now be evaluated.

4.3 Data Analysis and Results

Having demonstrated all key criteria for evaluating the study structural model, hypotheses $H1$ to $H4$ were tested via PLS-SEM path analysis with results summarised in Table 4.

The main effects hypotheses in the basic research model ($H1$ to $H4$) were tested using the entire 253 valid samples and all these hypotheses were supported by the data. The results confirmed that patients' personal motivation was positively and significantly influenced both by the quality of mHealth ($\beta = 0.591$, $p < 0.001$) and their opinion on mHealth ($\beta = 0.119$, $p < 0.001$), supporting hypotheses $H1$ and $H2$.

Patients' personal motivation is also shown to have a significant effect on adoption intention ($\beta = 0.490$, $p < 0.001$), supporting hypothesis $H3$. The results also indicated that social influence significantly affect both patients' personal motivation ($\beta = 0.273$, $p < 0.001$) and their adoption intention ($\beta = 0.219$, $p < 0.001$), supporting $H4a,b$.

Performing the IPMA to examine hypotheses $H5a,b$, the analysis yielded importance values of social influence by clinicians, family and friends, and other patients of 0.131, 0.089, and 0.081 respectively. Hence, the results confirmed hypotheses $H5a$ and $H5b$ that the influence of clinicians is relatively stronger than other social influencers on the patients' adoption intention.

Table 4. Summary of PLS-SEM path analysis

Path	Hypothesis	Path coefficients	t-statistics	p-values	Supported?
Quality of mHealth → personal motivation	H1	0.591	10.962	0.000**	Yes
Opinion on mHealth → personal motivation	H2	0.119	2.752	0.006**	Yes
Personal motivation → mHealth adoption intention	H3	0.490	7.642	0.000**	Yes
Social influence → personal motivation	H4a	0.273	4.983	0.000**	Yes
Social influence → mHealth adoption intention	H4b	0.219	2.956	0.003**	Yes
*p < 0.05; **p < 0.01					

Hypotheses *H6a,b,c* were further assessed via PLS-MGA among two subsamples: high v. low hospital usage group (n = 110; 143 respectively) to investigate the effect of hospital usage on the motivations-adoption relationship. Results, illustrated in Figure 2, revealed that no significant differences were found in the effects of the quality of mHealth and the opinion of mHealth on patients' personal motivation, as well as personal motivation on adoption intention regardless of their high v. low hospital usage.

As depicted, *H6a* has been rejected, so was *H6b*. Although social influence was related more strongly to the patient's personal motivation among high hospital usage group v. low usage group, the difference was significant only at $p < 0.1$. Conversely, *H6c* was supported as the effect of social influence on the adoption intention was significant among high hospital usage group ($p < 0.001$) but not with the low usage group ($p > 0.1$). The path coefficient difference between high usage group and low usage group is significant at $p < 0.05$.

Figure 2. Results of multi-group analysis

- Notes:
1. Significance level of β : ns – not significant; *p < 0.05; **p < 0.01; ***p < 0.001
 2. Path coefficient: β_H – high hospital usage; β_L – low hospital usage
 3. Significance level of path coefficient difference: z - β_H and β_L different significantly at $p < 0.05$

In summary, we may allude that the incorporation of motivation into mHealth adoption of hospital-provided mobile apps offers a focal point for hospital IT department and hospital management team to enhance mHealth adoption. Specifically, our study results identified and supported two main perspectives of mHealth adoption drivers: social centric (that is, those advocating mHealth to patients via social influencers) and patient-centric (that is, communicating and promoting mHealth to patients directly). We now move towards a closure of our study results, contributing to strengthening these two perspectives.

5. CONCLUSION

5.1 Discussion and Contributions

From a social-centric perspective, the advocacy from healthcare professionals, patients' family members and other patients are influential in a patient's mHealth adoption. Patient-to-patient recommendation seldom happens unless the patients are highly satisfied with the hospital service (Cheng, Yang, & Chiang, 2003). Therefore, patient-to-patient recommendation of mHealth adoption is currently scarce as the usage rate is low (9% of total respondents).

As clinicians are most influential among all social influencers for mHealth adoption, hospitals should consider promoting mHealth adoption via clinicians. However, clinicians and other healthcare professionals are too occupied in providing healthcare services so promoting mHealth apps to patients would be an added workload burden. Based on the results of this study, promoting mHealth to patients is effective only for patients with high hospital usage frequency. In light of this, hospital management could consider communicating the importance of mHealth adoption via clinicians to patients with high hospital usage, for example, in specialist out-patient clinics that serve patients with chronic diseases and high hospital usage.

From a patient-centric perspective, driving patients' personal motivation in mHealth adoption is observed to be more effective than investing effort into social motivation among patients with low hospital usage. To enhance the patients' personal motivation, undoubtedly the technical performance of hospital-provided mobile apps must be perceived by patients to be useful and easy to use.

Nonetheless, the mediating effect of patients' personal motivation indicates that the availability of useful hospital-provided apps is only part of the solution. Healthcare providers should go beyond the development of useful and easy-to-use mobile apps and invest resources in communicating to patients the benefits of using mHealth against the traditional ways of using hospital services and acquiring information.

In the settings of developed countries such as Hong Kong, patients are generally technology savvy so the major impediment of mHealth adoption originates from patients' motivation. However, over 60% of the patients surveyed are found to be unaware of the hospital-provided mobile apps or of their functionality. Promotion materials in the hospital are usually "overcrowded" and therefore may go unnoticed, as well as too wordy and informative to "motivate" patients. Thus, hospital IT departments and healthcare management teams are advised to implement effective mobile app promotion and communication activities aimed to enhance the patients' adoption motivation of mHealth.

5.2 Limitations

While this study contributes to the knowledge gap of the role of social influencer (clinicians in particular) in motivating the adoption of mHealth among patients with high hospital usage, there are a few limitations in this research to be addressed by future studies.

First, this study collected samples from a single hospital which is an acute hospital. Future research may examine patient samples from a range of hospital types such as rehabilitation, palliative care, and specialty hospital.

Second, this study was conducted before COVID-19 pandemic. However, the uptake of health apps and telehealth has been accelerated by the coronavirus disease (Torous, Myrick, Rauseo-Ricupero, & Firth, 2020). Thus, future research may explore if there are new factors in relation to social influence on mHealth adoption emerging from the coronavirus pandemic.

5.3 Future Research Directions

This study highlights personal motivation and social influence as crucial activation to the adoption of mHealth among patients. Policymakers should identify the key social influencer(s) so as to amplify the promotion effect of mHealth adoption. Moreover, it is crucial to understand the effect of these social influencers on the different audience segments based on patients' hospital usage for better mHealth communication.

So far, results of this study offer insights into the relationship between social influence, patients' personal motivation and mHealth adoption. There appears to be a significant positive effect of the influence of clinicians on mHealth adoption intention, which however, applies hugely to patients with frequent hospital usage. The study findings also show that patients are more motivated to adopt mHealth interventions with quality, regardless of their hospital usage frequency.

Altogether, to promote mHealth adoption effectively, policymakers should communicate mHealth adoption to all patients with a message focusing on the quality of mHealth interventions. This research had contributed to the knowledge gap in exploring the impact of social influence on mHealth adoption. Additionally, results of this study have enriched the theoretical concept in the interaction effect of social influence and patients' hospital usage characteristics. As such, hospital policymakers can also target mHealth promotion for high hospital usage group via clinicians to enhance the promotion effectiveness under limited resources. Hospital usage frequency, as a behavioral trait of patients, is much easier to be used in mHealth promotional communications to patients than other demographic variables such as age and gender. A key practical contribution of this study suggests adopting a series of pragmatic promotion tactics for mHealth adoption among hospital patients.

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