Factors Influencing Users' Willingness to Consult Chatbots for Health Information

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Abstract

Busy healthcare professionals often do not have enough time to provide their patients with comprehensive health education. As a solution, a small number of organizations have attempted to use chatbots to relay this information. Whether patients can accept this new technology, and what factors influence their willingness to engage with it, are still unclear. Using the theory of planned behavior, uses and gratification theory and involvement theory, this study explored the factors influencing the use of chatbots for health education. We conducted a questionnaire survey that generated 117 valid responses. Results showed that convenience, fashion and involvement all significantly influence user attitudes ($p<0.05$). Attitudes and subjective norms both have a significantly positive impact on intention ($p<0.05$). The results of this research can serve as reference for healthcare organizations in designing chatbots.

Keywords: Chatbots, health education, theory of planned behavior, uses and gratification theory

1. Introduction

1.1 Research Background

The development of new care models is an increasingly critical area of research, as many countries (e.g., Taiwan, Japan and the U.S.) struggle with an ageing population along with insufficient and overworked healthcare staff. Although health education is an important part of care, medical institutions have limited resources to provide patients with effective health education. The rapid development of chatbots presents a new solution to this issue. Health education means a process of learning that is intended to shift the knowledge, attitudes and skills of patients in a way that enables them to engage in healthy behaviors (Lawrence, 1975). The ultimate aim of health education is to improve health literacy, which refers to the ability to receive and process health information, make health-related decisions and follow treatment instructions (Nutbeam, 2000).

Since introducing a national health insurance system in 1995, Taiwan has seen a significant increase in utilization of health services. The accessibility and low cost of healthcare, coupled with a preference to attend large hospitals, means that patients usually spend far more time waiting in queues for their appointments and prescriptions compared to time spent consulting with doctors and healthcare staff. Overworked doctors do not have enough time to provide comprehensive health education. Over time, this leads to not only reduced patient satisfaction but potentially also reduced health literacy, ultimately leading to poorer compliance with treatment instructions and poorer outcomes.

In recent years, private corporations and hospitals in Taiwan have collaborated to develop chatbots as a solution to the problems described above. Using the chatbots, patients can ask health questions and submit a description of their symptoms to the doctor prior to the consultation. To the best of our knowledge, researchers have not yet explored the factors that influence how users (patients and non-medical staff) engage with chatbots for the purpose of health education. The U.S-based Pew Research Center reports that millions of Americans are searching for medical advice on the Internet (Fox, 2011). More than 79.2% of the population of Taiwan is connected to the Internet, with 96.8% using a smart phone and 99.2% using the communication application Line (which can serve as a platform for chatbots). We identified the need for an in-depth analysis into the key factors that influence users engaging with chatbots for health education.

1.2 Research Importance

A number of healthcare organizations have introduced health information systems (HIS) (World-Health-Organization, 2010), with many studies evaluating how to successfully integrate HIS (Heeks, 2006). Most of this research, however, focuses on how to assist healthcare staff (Haux, 2006) in managing patient information, monitoring wards in real time and making health-related decisions. Few researchers have studied the role of patients and non-medical staff, despite evidence demonstrating that patients can experience improved quality of life by practicing self-care with the support of HIS (Gustafson, 1999).

With the advancement of mobile devices, it is now easier for patients to practice self-care using mobile health (or m-health). In 2011, former U.S. Secretary of Health and Human Services Kathleen Sebelius referred to m-health as "the biggest technology breakthrough of our time" (Dolan, 2011). Studies have shown that m-health technology can be used to overcome current limitations in the healthcare environment, reducing costs and leading to improved outcomes (Steinhubl et al., 2013). Leveraging the widespread popularity of social networks, communication software and mobile networks (Liu et al., 2018), chatbots are particularly suited to m-health due to their convenience, accessibility and low operating costs. Existing research on chatbots has concentrated on natural language processing and artificial intelligence, with few studies exploring the application of chatbots to m-health or user behavior. We analyzed the factors influencing how users interacted with a health education chatbot we developed for this research. The results provide important reference for healthcare institutions.

1.3 Research Objective

We developed a health education chatbot for the purposes of this research and applied the Theory of Planned Behavior (Ajzen, 1985), Uses and Gratification Theory (Ruggiero, 2000) and Involvement theory (Zaichkowsky, 1986) to explore the factors impacting user interaction with the chatbot. The results provide valuable insight into the design, specification, and possibly the evolution of m-health systems and chatbots, which can reduce labor costs, alleviate resource pressures and increase patient knowledge, thereby improving health literacy and compliance.

2. Literature Review

2.1 Chatbots

A chatbot, also termed an artificial conversational entity, is a computer program that responds in textual, auditory or graphic format to messages input by a user (Ciechanowski et al., 2018; Fryer et al., 2017). Driven by the advancement of artificial intelligence, machine learning and natural language processing, chatbots can respond in an increasingly human-like manner and solve more complex sentences. Operating 24 hours without the limitations of human labor, chatbots can effectively help businesses reduce cost. Many instant communication platforms (such as Facebook Messenger and Wechat), e-commerce platforms, customer service and healthcare organizations are utilizing chatbots. Instead of learning to operate a complex system, users can interact with chatbots through simple dialogue, reducing the user threshold. The White House Messenger Bot, launched by the U.S. government in 2016 (Roston, 2016), enables the public to engage with government departments and even the U.S. president. Buoy Health rolled out a chatbot, Buoy, that asks patients questions to better understand their symptoms, suggests up to three possible diagnoses based on their answers, and then recommends nearby healthcare facilities. Similar chatbots include Chinese firm Baidu's Melody and Taiwan's Wan Xiaofang, developed by HTC and Taipei Municipal Wanfang Hospital. We developed a simple chatbot for the purposes of this research. Participants added the chatbot as a friend on Line and communicated through text messaging and screen commands.

2.2 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) is a useful theoretical model for interpreting or predicting human behavior (Blair, 1988). Ajzen (1991) proposed the concept that compared to beliefs and affection, behavioral intention is a stronger predictor of whether a person will engage in a particular behavior (for example, engage with a chatbot). Behavioral intention – the intention of a person to execute a specific behavior – is influenced by attitude, subjective norms and perceived behavioral control. In the context of this research, attitude refers to the positive or negative reaction of a person to a specific topic (receiving health education from a chatbot). Subjective norms refer to social pressure, whether significant others (healthcare professionals, family, partners and friends) believe a person should receive health education from a chatbot. Perceived behavioral control is an assessment of whether a person has the capability to carry out a task. In this context, it refers to the expectation that a person will be able to successfully engage with a chatbot for health education. Based on TPB, we propose the following hypotheses:

H1: User attitudes affect their intention to engage with the health education chatbot.

H2: Subjective norms affect user intention to engage with the health education chatbot.

H3: Perceived behavioral control affects user intention to engage with the health education chatbot.

2.3 Uses and Gratification Theory (UGT)

An audience-centered approach to mass communications research, Uses and Gratification Theory (UGT) posits that people seek out specific media to satisfy specific needs, rather than being passive consumers of media as suggested by traditional mass communication research (Ruggiero, 2000). In recent years, UGT has been widely applied to user behavior studies relating to instant messaging, online games, social media, smart phones and augmented reality. This study agrees that consumers opt into an information system to satisfy specific needs. The factors influencing their decisions include information (the capacity of the system to provide the user with accurate information) (Kaye & Johnson, 2004; Hicks et al., 2012); convenience (the user-friendliness of the system) (Hicks et al., 2012), and fashion (a feeling of novelty gained from using the system) (Leung, 2001). As many hospitals are experimenting with using chatbots for the purpose of health education, we defined these chatbots as an emerging information system. Based on UGT, information, convenience and fashion should have a significant and positive influence on the use of health education chatbots.

H4: The convenience of using a chatbot for health education positively influences attitude.

H5: The information to be gained from a health education chatbot positively influences attitude.

H6: The fashion of using a chatbot for health education positively influences attitude.

2.4 User Involvement Theory

Involvement is a psychological state. The more significant a product is perceived to be (in relation to needs, interests and values), the more involved the user becomes (Zaichkowsky, 1985). Research has shown that the more involved users are in the development and design of an information system, the more positive their attitudes, which in turn impacts subjective norms and ultimately increases their intention to use the system (Dale, 1975; Ives & Olson, 1984; Hartwick & Barki, 1994). Based on the above, we propose the following hypotheses:

H7: The involvement of users with health education chatbots positively influences their attitude.

H8: The involvement of users with health education chatbots positively influences subjective norms.

How closely patients comply with health instructions is critical to their recovery. Although much existing research on m-health and HIS has focused on healthcare professionals over patients, some studies have shown that mobile devices can assist in improving patient compliance (Tozzi et al., 2015; Wu et al., 2015). This study believes that using chatbots to deliver health education presents a solution to problems such as hospitals having insufficient resources to devote to health education, or poor compliance and health literacy on the part of patients. We conducted user behavior research based on the theoretical framework described above.

3. Methodology

3.1 Theoretical Framework

As illustrated in Figure 1, this study utilized the Theory of Planned Behavior (Ajzen, 1985), Uses and Gratification Theory (Ruggiero, 2000) and Involvement theory (Zaichkowsky, 1986) to explore the factors that influence how users interact with chatbots for health education.

3.2 Research Design

3.2.1 Participants

Randomly selected students from a university in Taiwan participated in a questionnaire survey. Over a two-month period, 132 questionnaires were collected, of which 117 were assessed as valid. Fifteen questionnaires were invalidated due to incomplete responses.

3.2.2 Questionnaire Design

Based on the supporting theoretical framework, we designed the questionnaire to measure each of the eight key constructs (see Figure 1). A seven-point Likert scale was used to measure response, with 1 = strongly disagree and 7 = strongly agree.

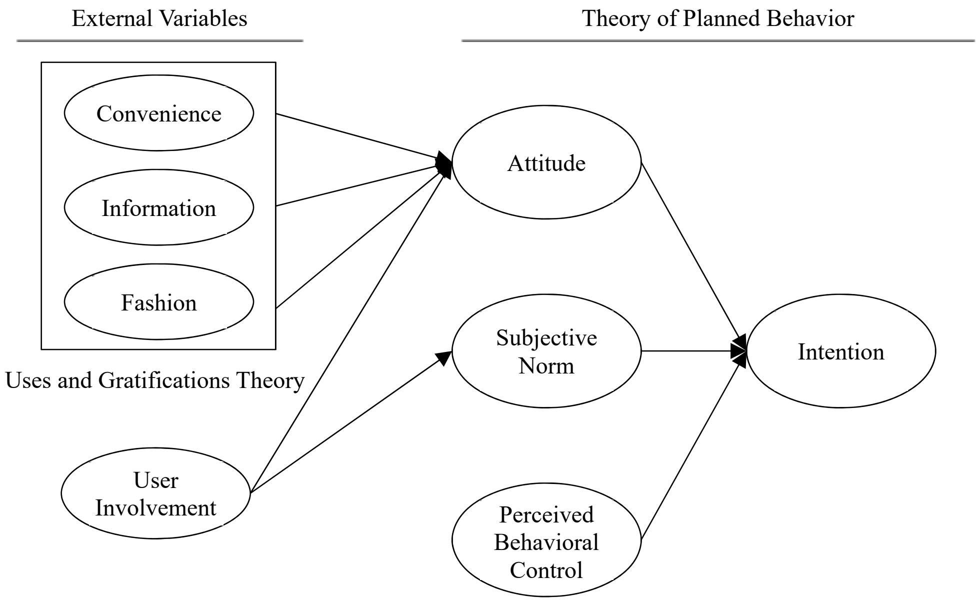

Figure 1: Theoretical Framework

3.2.3 Survey

Participants completed the survey after interacting with the health education chatbot and gaining a basic understanding of the process. The step-by-step procedures are set out in Table 1:

Table 1: Experiment Objectives and Procedures

Step	Description	Aim
1	Researchers explain the concept of the study, the process of the experiment and how to engage with the chatbot.	This step provides participants with a basic understanding of the system.
2	Participants open their Line application and add the chatbot as a friend using a QR code.	This step allows participants to evaluate the convenience and fashion of the system.
3	Select 'understand coronary heart disease' from the menu and receive a response from the chatbot.	This step determines whether participants can successfully operate the system by finding the menu and selecting the correct option. Users can assess the convenience and level of information provided by the system.
4	From select 'prevention 'from the response provided by the chatbot. The chatbot then generates information on preventing coronary heart disease.	This step evaluates whether participants can interact with the chatbot. Users can assess the convenience and level of information provided.
5	Select the keyboard icon in the lower left-hand corner to switch to text input mode. Type 'hahaha'in response to the chatbot.	This step evaluates whether participants can locate the keyboard icon on the interface and engage in dialogue with the chatbot. Users can evaluate the convenience and fashion of the system.
6	Input any words or phrases and send as a message to the chatbot.	This step enables participants to evaluate convenience and their level of involvement with the chatbot.
7	Input 'symptoms of gastroenteritis', generating a response from the chatbot	This step allows participants to evaluate convenience, information and involvement.

Note: The above process is designed to enable participants to evaluate the constructs of convenience, fashion, information and user involvement in engaging with health education through a chatbot.

3.2.4 Data Analysis

Partial least squares structural equation modelling (PLS-SEM) was used to analyse the hypothesized model in this study. PLS-SEM is considered appropriate for this study as it permits the simultaneous estimation of multiple causal relationships between more independent variables and one or more dependent variables (Hair et al., 2017). Moreover, various studies (e.g., F. Hair Jr et al., 2014; Henseler & Fassott, 2010) indicate that PLS-SEM present a good methodological approach for hypotheses testing in case researchers deal with small sample size (i.e., <200). Previous studies (e.g., Henseler & Fassott, 2010) demonstrate that PLS-SEM allows researchers to work with smaller sample sizes without losing its statistical power. Regarding sample size requirements, the 117 responses collected in this study exceeds the requirements of ten times the largest number of formative indicators used to measure one construct in the structural model (Hair et al., 2011). The collected data was coded into SPSS 20 for statistical analyses and correlations prior to the PLS-SEM analysis. Statistical significance of structural paths was examined through the bootstrap procedure, using 5000 resamples.

4. Results

4.1 Demographics

Table 2 lists the demographic variables of the 117 participants, 58% of whom were male (n=68) and 42% female (n=49). The majority were aged between 18-24 years (n=110,94%), and 62% were educated to postgraduate level or above (n=73), with another 38% being college graduates (n=44). Importantly, 97% (n=113) had used Line.

Table 2: Demographic Variables (N=117)

Variable	Attribute	N	Percentage
Sex	Male	68	58%
	Female	49	42%
Age	18-22 years	44	38%
	23-24 years	66	56%
	> 25 years	7	6%
Education	Undergraduate	44	38%
	graduate	73	62%
Have you used Line?	Yes	113	97%
	No	4	3%

4.2 Assessment of Measurement Model

Outer loadings, average variance extracted (AVE), composite reliability (CR), and discriminant validity were calculated to examine the measurement models (Hair et al.,2017). As shown in Table 3, almost all the outer loadings of the reflective constructs exceed the recommended 0.70 minimum and exhibit sufficient t-values (Hair et al., 2017). For average variance extracted (AVE), all constructs exceed the recommended minimum threshold of 0.50, therefore establishing the convergent validity of the measurement model. Furthermore, the values for composite reliability (CR) and Cronbach's alpha exceed the minimum threshold value of 0.70 that confirms the high reliability of the constructs. The criterion of Fornell-Larcker (1981) was used to assess discriminant validity in this study. According to this criterion, square root of AVE should be greater than the correlations of the constructs with all other construct in the structural model. As shown in Table 4, the off-diagonal values are the correlations between the latent constructs and the diagonal values in bold are the square root of AVE. As all the diagonal value is greater than the values in its row and column, the discriminant validity is well established.

Table 3: Construct Validity and Reliability

Research construct	Item	Outer loading	AVE	Composite reliability (CR)	Cronbach's alpha	Outer loadings t-statistics
Intention	INT 1	0.885	0.839	0.940	0.904	46.701
	INT 2	0.915				80.371
	INT 3	0.947				42.579
Attitude	ATT 1	0.927	0.854	0.946	0.915	65.238
	ATT 2	0.918				49.515
	ATT 3	0.928				64.387
Subjective norms	SN 1	0.913	0.804	0.925	0.877	42.394
	SN 2	0.930				65.500
	SN 3	0.845				24.804
Perceived behavioral control	PBC 1	0.924	0.643	0.834	0.71	42.579
	PBC 2	0.925				43.352
	PBC 3	0.469				3.795
Convenience	CON 1	0.910	0.706	0.877	0.785	45.735
	CON 2	0.906				35.739
	CON 3	0.686				8.865
Information	IN 1	0.878	0.784	0.916	0.861	37.066
	IN 2	0.928				46.701
	IN 3	0.849				80.3711
Fashion	FA1	0.908	0.783	0.916	0.862	48.880
	FA2	0.908				56.027
	FA3	0.838				16.640
User involvement	UI 1	0.909	0.797	0.922	0.873	49.535
	UI 2	0.905				56.225
	UI 3	0.865				22.896

Table 4: Discriminant Validity

Research construct	Intention	Attitude	Subjective norms	Perceived behavioral control	Convenience	Information	Fashion	User involvement
Intention	**0.916**	0.760	0.693	0.589	0.518	0.676	0.642	0.723
Attitude		**0.924**	0.591	0.509	0.571	0.712	0.646	0.715
Subjective norms			**0.897**	0.480	0.443	0.518	0.522	0.66
Perceived behavioral control				**0.802**	0.517	0.498	0.499	0.481
Convenience					**0.840**	0.670	0.528	0.535
Information						**0.885**	0.573	0.54
Fashion							**0.885**	0.610
User involvement								**0.893**

[a] The off-diagonal values in the above matrix are the square correlations between the latent constructs and diagonal are square root of AVE

4.3 Assessment of Structural Model

The structural model from the PLS analysis is summarized in Table 5 and Figure 2. All hypotheses apart from H4 were supported. The attitudes (β=0.470, p<0.001) and subjective norms (β=0.314, p<0.01) of users significantly influenced their intention to use chatbots for health education. User attitude is significantly influenced by how informative (β = 0.398, p < 0.001) and fashionable (β = 0.180, p < 0.05) the chatbot is perceived to be, and how involved the users are in the process (β = 0.390, p < 0.001). Finally, user involvement (β = 0.657, p < 0.001) has a significant positive effect on subjective norms. The structural model explains 69.6% of the variance in intention (R^2=0.696), 67.9% of that in attitude (R^2=0.679), and 43.6% of that in subjective norms (R^2 = 0.436).

Table 5: Result of Hypothesis Testing and Structural Relationships

Hypothesis	Path	Path coefficients	t-statistic	p value	Inference
H1	Attitude → Intention	0.470***	4.887	0.000	Supported
H2	Subjective norms→ Intention	0.314**	3.283	0.001	Supported
H3	Perceived behavioral control → Intention	0.198**	2.893	0.003	Supported
H4	Convenience → Attitude	0.001	0.006	0.995	Rejected
H5	Information → Attitude	0.398***	3.964	0.000	Supported
H6	Fashion → Attitude	0.180*	2.104	0.032	Supported
H7	User involvement → Attitude	0.390***	4.759	0.000	Supported
H8	User involvement → Subjective norms	0.657***	10.240	0.000	Supported

(* p < 0.05, ** p < 0.01, *** p < 0.001)

Table 6: Results of R^2 and Q^2.

Endogenous latent constructs	R^2	Q^2
Intention	0.696	0.539
Attitude	0.679	0.533
Subjective norms	0.436	0.325

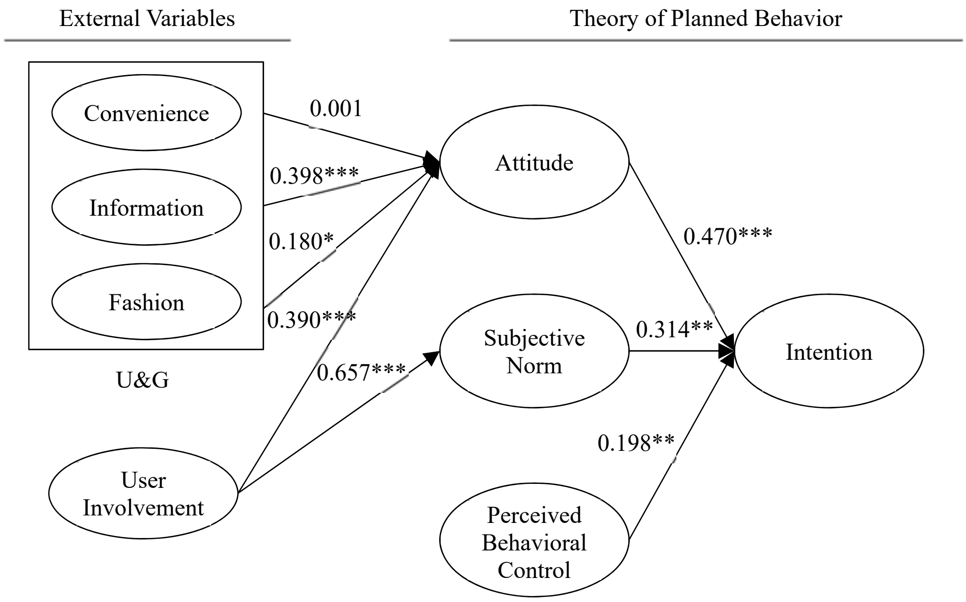

Figure 2: Estimated Causal Relationships of Structural Models
(* p < 0.05, ** p < 0.01, *** p < 0.001)

5. Discussion and Conclusion

5.1 Discussion

5.1.1 Theory of Planned Behavior (TPB)

Among the three constructs that make up TPB, attitude had the most significant impact on intention, with users considering how desirable and beneficial the behavior would be to themselves. These results are consistent with the research of Hung et al. (2012) on acceptance of health information systems. Subjective norms were also shown to significantly affect intention. This means that users consider the opinions of people important to them (doctors, family members, friends and partners) when deciding whether to use chatbots for health education. Perceived behavior control is an assessment of whether a person can execute a specific action. In this context, it refers to whether a person has adequate resources, opportunities or capability to use a chatbot for health education. We found that perceived behavioral control also had significant influence on intention. Furthermore, more than 95% of participants expressed above average satisfaction with perceived behavioral control, which could indicate that engaging with the health education chatbot is a very simple process.

5.1.2 Uses and Gratification Theory (UGT)

The current work presents that information had the most significant influence on attitude. It shows that, when users think that they can access the right information for their needs (e.g. to make health care decisions for family members), their attitude towards using the chatbots will be quite positive. This is consistent with the findings of Umit et al. (2009). The second most important factor is fashion. As noted by previous studies (e.g., Choi and Kim, 2016), users are more attracted to a technology if it is perceived as fresh and novel, which indirectly impacts their intention; Compared with traditional health education, obtaining health information through chatbots may be more fashionable. Finally, convenience did not significantly impact attitude, although over 90% of respondents expressed above average satisfaction with the convenience of using chatbots for health information. This could be because, when compared to information and fashion, convenience is less important to users. Previous studies in electronic commerce (e.g., Henderson and Divett, 2003) have shown similar results. Based on the above results, researcher recommended that healthcare organizations should focus on health care information and fashion to differentiate their chatbots.

5.1.3 User Involvement Theory

Involvement significantly influenced both attitude and subjective norms. This means that the more important it is to engage with health education chatbots, the more positively both the user and others (doctors, family, friends and partners) will feel about the behavior.

5.2 Contributions

The key contributions of the study are as follows: (1) practical contributions: Healthcare organizations should focus on attributes of fashion and convenience when developing chatbots. Healthcare staff should promote and communicate to patients the importance of using chatbots for health education, which can help to alleviate their resource pressures; (2) academic contributions: The results of this study contribute to filling knowledge gaps in research on self-care, the use of emerging technology (chatbots) in m-health, and user behavior relating to chatbots.

5.3 Limitations

The major limitations of the study are as follows: (1) The results of this study are limited to participants aged 18-24, educated to a university or postgraduate level. Future studies can consider a broader sample group with a wider range of ages, and extend the research to examine how users of different ages respond to chatbots; (2) The chatbot developed by this study is relatively simple to operate. Participant responses to the questionnaire may have been influenced by experiential limitations.

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