Analysis of Users' Continuous Usage Intention for mHealth Apps from an Information Ecology Perspective (Postprint)

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Abstract

Purpose: To investigate the factors influencing continuance intention of mobile health APPs and their underlying mechanisms. **Method:** From the perspective of information ecology, this study analyzes four categories of influencing factors: information, information person, information technology, and information environment, and proposes research hypotheses and constructs a research model based on the Expectation-Confirmation Model. **Results:** Multiple mobile health APP users were selected as participants, and 288 valid data points were collected through a "log tracking experiment + questionnaire survey" approach, with the model tested using SmartPLS 2.0. The results show that the relationships in the Expectation-Confirmation Model hold true in the mobile health context; information accuracy and consistency, information person' s perceived health threat, information technology' s ease of use and responsiveness, and the direct and indirect network externalities of the information environment all positively promote expectation confirmation and perceived usefulness of mobile health APPs; while information person' s e-health literacy positively promotes expectation confirmation but negatively inhibits perceived usefulness. **Limitations:** The experimental sample size needs to be expanded, and the conclusions drawn need to be further generalized. **Conclusion:** Users' continuance behavior with mobile health APPs is the result of the joint action of information, information person, information technology, and information environment.

Full Text

Analyzing Continuance Intention of Health APP Users Based on Information Ecology

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Abstract

[**Objective**] This study investigates the factors influencing users' continuance intention toward mobile health applications and their underlying mechanisms. [**Methods**] From an information ecology perspective, we analyzed four categories of influencing factors: information, information users, information technology, and information environment. Based on the Expectation Confirmation Model, we proposed research hypotheses and constructed a theoretical model. [**Results**] We recruited users of multiple mobile health applications as participants and collected 288 valid data points through a combination of log-tracking experiments and questionnaires, which were analyzed using SmartPLS 2.0. The results indicate that all relationships in the Expectation Confirmation Model hold in the mobile health context. Information accuracy and consistency, users' perceived health threats, technology responsiveness and ease of use, and both direct and indirect network externalities of the information environment all positively influence expectation confirmation and perceived usefulness. Meanwhile, users' eHealth literacy positively affects expectation confirmation but negatively influences perceived usefulness. [**Limitations**] The sample size needs expansion, and the conclusions require further validation. [**Conclusions**] Users' continuance behavior regarding mobile health applications results from the joint effects of information, information users, information technology, and information environment.

Keywords: Mobile Health; Continuance Intention; Information Ecology

1. Introduction

With the development of mobile information technology, increasing sub-health populations, the trend of chronic diseases affecting younger individuals, and intensifying population aging, mobile health has become a research and industry focus in recent years. Mobile health refers to the provision of medical and health services through wireless mobile communication technology [1], which can improve healthcare efficiency and significantly reduce medical costs [2]. According to the *2016 China Mobile Health Market Annual Research and Analysis Report* [3], by the end of 2015, China' s mobile health market had reached 4.88 billion RMB, with total mobile health users exceeding 17 million, among which mobile health applications represent the primary form of mobile health services.

Research on mobile health adoption and usage behavior can be categorized into four areas: (1) **Mobile health information service quality research**. Akter et al. proposed a mobile health service quality model, validating and evaluating mobile health service quality across three dimensions: system quality, interaction quality, and information quality [4]. Liu et al. found that information quality significantly promotes consumers' initial trust in mobile health services [5]. (2) **Individual-level influencing factors**. Zhang et al., integrating the Theory of Reasoned Action, found that gender significantly moderates the effects of facilitating conditions, attitudes, and subjective norms on mobile health adoption intention [6]. Guo et al., based on Protection Motivation Theory, verified the significant impact of perceived susceptibility, perceived severity, response efficacy, and self-efficacy on mobile health usage attitudes, along with moderating effects of age and gender [7]. Rai et al. validated the influence of service innovativeness, perceived health status, demographic variables, and socioeconomic status on mobile health usage intention [8]. (3) **Technology-level influencing factors**. Hung et al., based on the Technology Acceptance Model, explored the significant effects of perceived usefulness and perceived ease of use on mobile health management service adoption attitudes and intentions [9]. Cho integrated the Technology Acceptance Model and Expectation Confirmation Model to examine health application continuance usage [10]. (4) **Group-level influencing factors**. Hsiao et al. confirmed the influence of subjective norms on mobile health technology acceptance intention [11], while Yin et al. found that group influence significantly promotes users' health application usage intention [12].

Our thematic analysis of the literature reveals two areas for further exploration: First, **systematic research from an information ecology perspective**. Most existing studies rely on classic information systems theories such as TAM, examining mobile health user behavior from a single perspective—whether mobile health information service characteristics, user individual characteristics, technology characteristics, or usage environment characteristics. While this single-level approach facilitates detailed research, it may overlook other factors and their interactions. In reality, adoption of emerging health information services and technologies like mobile health results from comprehensive interactions among information service quality, medical application systems, user characteristics, and platform environments. Therefore, research from a holistic information ecology perspective is needed to derive more generalizable conclusions. Second, **sample collection through "experiment + questionnaire" methods**. Most existing empirical studies rely solely on questionnaires, which introduces sample bias and limits conclusions. This study recruited participants from online medical communities and offline channels, combining experimental and questionnaire methods to enhance data authenticity and reliability, yielding more generalizable and comprehensive conclusions.

Based on this analysis, we adopt an information ecology perspective, extracting four influencing factors—information, information users, information technology, and information environment—based on consumer and product characteristic analysis. Integrating the Expectation Confirmation Model, we propose research hypotheses and construct a model to explore mobile health application users' continuance intention. By recruiting mobile health users as experimental subjects and employing combined experimental and questionnaire methods for data collection, we validate hypotheses and the model using SmartPLS 2.0, providing actionable recommendations for developers, operators, and managers of mobile health applications.

2. Theoretical Foundation

2.1 Expectation Confirmation Theory

Oliver first proposed Expectation-Confirmation Theory (ECT) in 1980, suggesting that consumers judge satisfaction by comparing pre-purchase expectations with actual product performance [13]. Widely applied in consumer behavior research, ECT has been extended by many scholars. In 2001, Bhattacherjee proposed the Expectation Confirmation Model (ECM) for information systems contexts to explain continuance behavior [14]. ECM posits that perceived usefulness and expectation confirmation affect satisfaction, which in turn promotes continuance intention, while confirmation also influences perceived usefulness, which directly promotes continuance intention.

2.2 Information Ecology Theory

In 1999, Nardi and O'Day introduced the concept of "information ecology," defining it as "a system of people, practices, values, and technologies in a particular local environment" [15]. This theory examines the coordinated development of people, information, information technology, and information environment, representing the sum of information resources and their interrelationships within a certain scope. Wang et al. define information ecology as the transmission and feedback activities between information users and information environment supported by information resources through information technology to achieve equilibrium, identifying information, information users, information technology, and information environment as four key factors [16-17].

Mobile health applications can be viewed as independent and complete information systems with distinct health information dissemination characteristics. Supported by mobile internet and other information technologies, medical applications and healthcare professionals provide health information services to users. Meanwhile, health community features within mobile health applications create an information environment for users to share information and communicate with others. Thus, health information disseminated through medical applications, supporting technologies, users on the platform, and the information environment constitute a complete and complex information ecosystem through interactions among various information ecology factors. Users' mobile health application usage behavior is influenced not only by their own characteristics but also by information characteristics, technology features, and information environment. How to promote coordinated development among users, information, information technology, and information environment to better meet user needs and improve satisfaction represents an information ecology challenge for mobile health applications.

This study integrates the Expectation Confirmation Model and Information Ecology Theory, treating expectation confirmation, perceived usefulness, and satisfaction as variables affecting continuance intention, while considering the four information ecology factors (information, information users, information technology, and information environment) as external factors influencing expectation confirmation and perceived usefulness. Through empirical research, we explore how information ecology factors affect mobile health application continuance intention.

3. Research Hypotheses and Model

3.1 Hypotheses for the Expectation Confirmation Model

In the mobile health context, users develop satisfaction or dissatisfaction by comparing the effort expended using mobile health applications with the rewards obtained. Expectation confirmation, the gap between pre-use expectations and post-use performance, represents an important antecedent of satisfaction. Perceived usefulness, first proposed by Davis in 1989, is defined in this study as users' perception of the degree to which mobile health applications improve their health status and facilitate health management [18]. Cho integrated the Technology Acceptance Model and Expectation Confirmation Model to explore post-adoption behavior of health applications, finding that all original hypotheses in the expectation confirmation model held [10]. Therefore, we propose:

H1: Satisfaction positively influences continuance intention toward mobile health applications.
H2: Expectation confirmation positively influences satisfaction with mobile health applications.
H3: Expectation confirmation positively influences perceived usefulness of mobile health applications.
H4: Perceived usefulness positively influences satisfaction with mobile health applications.
H5: Perceived usefulness positively influences continuance intention toward mobile health applications.

3.2 Hypotheses for Information Factors

Information factors include information accuracy and information consistency. Based on Johnson et al., information accuracy is defined as users' perception of the correctness of health information published on mobile health applications [19]. Based on Chou et al., information consistency is defined as users' perception of the similarity or consistency between information provided by mobile health applications and information from other sources on the same topic [20]. Gudigantala et al. found that information accuracy promotes perceived system effectiveness [21], while Chou et al. found that perceived knowledge consistency promotes knowledge adoption behavior in virtual communities [20]. We argue that higher perceived accuracy and consistency of health information provided by mobile health applications lead to higher expectation confirmation and stronger perceived usefulness.

H6(a): Information accuracy positively influences expectation confirmation of mobile health applications.
H6(b): Information accuracy positively influences perceived usefulness of mobile health applications.
H6(c): Information consistency positively influences expectation confirmation of mobile health applications.
H6(d): Information consistency positively influences perceived usefulness of mobile health applications.

3.3 Hypotheses for Information User Factors

Information user factors include perceived health threat and eHealth literacy. Perceived health threat derives from Protection Motivation Theory (PMT), which explains health technology and service adoption behavior through health threat assessment and coping assessment [22]. When users believe they will encounter health threats or that such threats pose significant health risks, they tend to adopt relevant health technologies or services to mitigate these threats. We argue that stronger perceived health threat leads to stronger expectation confirmation and perceived usefulness of mobile health applications.

eHealth literacy refers to users' ability to seek, find, evaluate, integrate, and apply needed information to solve health problems in internet environments, encompassing traditional literacy, health literacy, information literacy, scientific literacy, media literacy, and computer literacy [23]. Compared to offline medical service models, using the internet to find health information and receive health services yields similar effects with higher efficiency [24-25]. Users with higher eHealth literacy are more familiar with healthcare support technologies and tools such as computers, social media, and online medical platforms, and possess stronger abilities to search for, evaluate health information and services, and solve health problems, leading to better fulfillment of expectations regarding mobile health applications. However, users with higher eHealth literacy can proficiently use multiple tools and platforms to solve health problems, reducing their dependence on mobile health applications and weakening their perceived usefulness.

H7(a): Perceived health threat positively influences expectation confirmation of mobile health applications.
H7(b): Perceived health threat positively influences perceived usefulness of mobile health applications.
H7(c): eHealth literacy positively influences expectation confirmation of mobile health applications.
H7(d): eHealth literacy negatively influences perceived usefulness of mobile health applications.

3.4 Hypotheses for Information Technology Factors

Information technology factors include responsiveness and ease of use. Responsiveness is defined as mobile health applications' ability to actively respond to user needs and provide immediate services [26]. Based on Davis' s Technology Acceptance Model, ease of use is defined as the degree to which users believe that using mobile health applications reduces wasted effort [18]. Du et al. found that responsiveness positively influences perceived usefulness of SaaS [27], while Wu et al. found that perceived ease of use of mobile health systems positively influences perceived usefulness among healthcare professionals [28]. We argue that better perceived responsiveness and ease of use lead to stronger expectation confirmation and perceived usefulness.

H8(a): Responsiveness positively influences expectation confirmation of mobile health applications.
H8(b): Responsiveness positively influences perceived usefulness of mobile health applications.
H8(c): Ease of use positively influences perceived usefulness of mobile health applications.

3.5 Hypotheses for Information Environment Factors

Network externalities are used to examine the platform information environment, referring to the phenomenon where the value individual users derive from products or services increases as the number of users grows, including direct and indirect network externalities [29]. In the mobile health context, direct network externalities refer to users' perception of the number of ordinary users and doctors on medical applications, while indirect network externalities refer to users' perception that the medical application provides complementary tools or services. Zhou' s research indicates that both direct and indirect network externalities positively influence perceived usefulness [30]. We argue that more doctors and users on mobile health applications create greater user value and enhance expectation confirmation and perceived usefulness. Additionally, supplementary functions or services (such as health management tools and health discussion communities) greatly enhance expectation confirmation and perceived usefulness.

H9(a): Direct network externalities positively influence expectation confirmation of mobile health applications.
H9(b): Direct network externalities positively influence perceived usefulness of mobile health applications.
H9(c): Indirect network externalities positively influence expectation confirmation of mobile health applications.
H9(d): Indirect network externalities positively influence perceived usefulness of mobile health applications.

Based on these hypotheses, the research model is constructed as shown in Figure 1.

[Figure 1: see original paper]

4. Research Methodology

4.1 Experimental Design

We employed a combination of log-tracking experiments and questionnaires to ensure authentic and reliable data. After extensive literature review and market research, we selected "Chunyu Doctor" as the experimental material for three reasons: (1) It has a large user base in China's mobile health application market [3]; (2) While primarily focused on online light consultation and self-diagnosis, it also provides health information dissemination, self-health management assistance, and online appointment registration, making it representative and suitable for our research requirements.

The research team designed experimental instruction documents, task documents, and log documents, which were published on a domestic online survey platform. The instruction documents briefly introduced the experimental purpose and procedures, enabling participants to understand the current state of mobile health development and install/register the "Chunyu Doctor" application on their phones. Each morning, researchers sent task documents to participants, containing instructions for deep exploration of specific functions, which had to be completed by day' s end. Participants filled out log documents each evening to record task completion. Experimental tasks involved browsing health information, using health management tools, self-diagnosis, and online light consultation. The experiment lasted five days, with participants receiving monetary compensation upon completion.

4.2 Questionnaire Design and Data Collection

The questionnaire included demographic variables and measurement items. To ensure reliability and validity, all items were adapted from existing literature and tailored to our research context. Table 1 shows the questionnaire variables and corresponding items.

All items were measured using a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). To ensure data accuracy and scientific rigor, we conducted a pre-test with 30 university student users of mobile health applications before large-scale distribution. The pre-test results were reviewed by three mobile health research experts for questionnaire revision, with repeated testing until feedback was within acceptable ranges, after which large-scale experiments and surveys were conducted.

Participants experienced the selected medical application for five days, with tasks and log documents ensuring completion. We recruited 320 volunteers, distributed experimental instructions, and began formal experiments after confirming understanding and consent. Upon completion, final questionnaires were distributed. After eliminating incomplete or obviously erroneous responses, 288 valid questionnaires were obtained. Participants were recruited through online medical websites and forums, as well as offline interviews. To ensure representativeness and validity, potential participants were screened via email or interview regarding their health needs or mobile health experience, selecting those with high health needs or prior experience. Since this study examines continuance intention, participants with prior experience were included to better reflect actual usage patterns.

4.3 Sample Description

As shown in Table 2, among the 288 valid questionnaires, males accounted for 53.8% and females 46.2%. Age distribution showed that those 25 and under comprised the largest group (over 85%), ages 26-45 accounted for about 10%, and those 46 and above comprised 4.5%. In terms of education, undergraduates represented the largest group at 64.9%, junior college and below accounted for 31.0%, and master' s degree and above comprised 4.1%.

5. Data Analysis and Results

Model validation included measurement model testing and structural model testing, analyzed using SmartPLS 2.0. This software employs partial least squares, requiring smaller sample sizes and making fewer distributional assumptions. We first ran the PLS Algorithm to validate the measurement model, then used Bootstrapping to analyze the structural model.

5.1 Measurement Model Validation

Measurement model assessment included reliability and validity testing. Reliability, indicating whether scale results are trustworthy, was assessed through Composite Reliability (CR) and Cronbach' s alpha values. Validity includes convergent and discriminant validity. Convergent validity, examining the correlation between items and their corresponding variables, was assessed through Average Variance Extracted (AVE). Discriminant validity, testing whether items correlate more strongly with their intended variables than with others, was assessed by comparing the square root of each variable' s AVE with inter-variable correlations.

Tables 3 and 4 show reliability, convergent validity, and discriminant validity results. Table 3 indicates that all factor loadings exceed 0.7, all CR values exceed 0.7, and Cronbach' s alpha values range between 0.8896 and 0.9588, demonstrating good reliability. All AVE values exceed 0.5, indicating good convergent validity. Table 4 shows that the square root of each variable' s AVE (diagonal values) exceeds its correlations with other variables (off-diagonal values), demonstrating good discriminant validity.

5.2 Structural Model Validation

Hypothesis testing was based on path coefficients and significance levels. Bootstrapping was applied to calculate path coefficients, with 1,000 resamples to test significance, as shown in Figure 2.

[Figure 2: see original paper]

Figure 2 reveals that satisfaction positively influences continuance intention (path coefficient = 0.714). Expectation confirmation positively influences satisfaction and perceived usefulness (path coefficients = 0.690 and 0.159, respectively). Perceived usefulness positively influences satisfaction and continuance intention (path coefficients = 0.280 and 0.141, respectively). Thus, all relationships in the Expectation Confirmation Model hold, supporting H1, H2, H3, H4, and H5.

Information accuracy significantly and positively influences expectation confirmation and perceived usefulness (path coefficients = 0.349 and 0.231). Information consistency positively influences perceived usefulness but not expectation confirmation (path coefficients = 0.291 and 0.049). Therefore, H6(a), H6(b), and H6(d) are supported, while H6(c) is not.

Users' perceived health threat positively influences expectation confirmation and perceived usefulness (path coefficients = 0.099 and 0.059). eHealth literacy positively influences expectation confirmation but negatively influences perceived usefulness (path coefficients = 0.116 and -0.142). Thus, H7(a), H7(b), H7(c), and H7(d) are all supported.

Regarding information technology factors, responsiveness positively influences expectation confirmation and perceived usefulness, while ease of use positively influences perceived usefulness (path coefficients = 0.213, 0.116, and 0.133, respectively). Therefore, H8(a), H8(b), and H8(c) are supported.

Regarding information environment factors, direct network externalities positively influence expectation confirmation and perceived usefulness, while indirect network externalities positively influence perceived usefulness but not expectation confirmation (path coefficients = 0.151, 0.053, 0.116, and -0.005). Thus, H9(a), H9(b), and H9(d) are supported, while H9(c) is not.

R^2 represents the explanatory power of independent variables on dependent variables. In user behavior research, $R^2 > 0.20$ indicates high explanatory power. Results show R^2 values of 0.680 for expectation confirmation, 0.851 for satisfaction, 0.809 for perceived usefulness, and 0.695 for continuance intention, indicating good model fit and high predictive power.

6. Discussion and Implications

From the perspective of the Expectation Confirmation Model, consistent with previous research [10], users' expectation confirmation positively influences their perceived usefulness and satisfaction with mobile health applications, while perceived usefulness promotes satisfaction. Both perceived usefulness and satisfaction jointly promote continuance intention.

From a holistic information ecology perspective, users' continuance intention toward mobile health applications results from the combined effects of information, information users, information technology, and information environment. Hsiao et al. [11] examined mobile health technology adoption among elderly populations from technology, individual, and social perspectives, while Cho et al. [36] investigated college students' health application usage intention from individual health characteristics and group influence perspectives. Building on previous work, this study integrates four critical dimensions from an information ecology perspective, revealing the joint influence of these core elements on continuance intention and expanding the sample across age groups to derive more generalizable conclusions.

Regarding information factors, extending Liu et al.' s [5] research, we found that users' perception of health information correctness enhances their expectation confirmation and perceived usefulness. Additionally, when health information on applications is similar to that obtained from other channels, perceived usefulness strengthens. However, regarding user expectations, obtaining health services and self-health management represent primary expectations, with less emphasis on information consistency. In some contexts, obtaining health information different from other channels may better meet needs for information diversity, explaining why information consistency does not significantly influence expectation confirmation.

Regarding information user factors, building on Guo et al. [2] and Cho et al. [10], we found that perceived health threat and eHealth literacy jointly influence expectation confirmation and perceived usefulness. Perceived health threat reflects users' perception of disease susceptibility and severity; stronger perceived health threat leads to stronger expectation confirmation and perceived usefulness. Conversely, users with high eHealth literacy can easily use application functions and services, fulfilling their expectations. However, higher eHealth literacy enables users to find better health solutions through other channels, weakening their perceived usefulness of mobile health applications.

Regarding information technology factors, extending Hung et al.' s [9] research, we found that system ease of use and responsiveness jointly influence perceived usefulness. Responsiveness reflects whether applications can quickly respond to user requests and provide service feedback; better responsiveness strengthens expectation confirmation and perceived usefulness. Consistent with the original TAM model, easier learning and use of mobile health applications enhance perceived usefulness.

Regarding information environment factors, Zhang et al. [6] validated the influence of subjective norms on mobile health adoption attitudes. However, in China's mobile health context, where market penetration remains relatively low, users are more concerned about whether sufficient doctors and users exist on medical applications to provide references for medical consultation, and whether supplementary tools facilitate health management. Thus, direct and indirect network externalities play important roles in continuance intention. More doctors and users enable greater value through increased communication, enhancing expectation confirmation and perceived usefulness. Supplementary health management tools also enhance perceived usefulness. However, since users' primary purpose is obtaining health information and services, supplementary functions do not significantly influence expectation confirmation.

Based on these findings, developers, operators, and managers of mobile health applications can derive several implications from an information ecology perspective:

(1) For developers: Focus on information technology and environment to enhance perceptions of ease of use, responsiveness, and indirect network externalities. While Hung et al. [9] emphasized ease of use and usefulness, developers should also thoroughly investigate users' health information service needs, identify product positioning, and develop functional modules and supplementary health management tools that meet diverse user needs. Through "personalized" functional services, developers can enhance expectation confirmation, usefulness, and satisfaction. Additionally, they should ensure system responsiveness and ease of use, developing products that users can easily understand and master while avoiding instability or crashes. Creating Q&A knowledge bases from frequently asked questions can enable automatic responses or health service recommendations based on user inquiries, effectively reducing waiting time.

(2) For operators: Focus on information and information users to leverage information accuracy, consistency, and perceived health threat. Previous research offered limited practical suggestions regarding health information. Our findings indicate that operators should enhance perceived accuracy and consistency by labeling health information sources, institutions, and reliability levels when publishing health updates. Building on Guo et al. [7], who suggested demonstrating cases of user benefits or health risks from non-use, operators can also identify users' perceived health threat levels based on registration, browsing, and service usage history, providing targeted care and assistance to those with strong health threat perceptions through personalized medical information or doctor recommendations, encouraging use of application health services.

(3) For managers: Focus on information users and environment, emphasizing eHealth literacy and direct network externalities. While Cho et al. [36] found eHealth literacy did not significantly influence ease of use, our research reveals its positive effect on expectation confirmation. Managers can actively cultivate users' eHealth literacy by popularizing mobile health knowledge, encouraging participation in community discussions, and using multimedia tools for online consultations. They should also reduce application usage difficulty through engaging guides (e.g., animated tutorials) to enhance expectation confirmation among users with lower eHealth literacy. Building on Zhou [30], managers can increase doctor and user numbers to enhance user value benefits.

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Author Contributions

Zhang Min and Luo Meifen: Conceived the research idea and designed the study; Luo Meifen and Nie Rui: Conducted experiments and collected questionnaires; Luo Meifen: Cleaned and analyzed data; Luo Meifen: Drafted the manuscript; Zhang Min and Zhang Yan: Revised the final version.

Conflict of Interest Statement

All authors declare no conflict of interest.

Supporting Data

Supporting data is self-archived by the authors, E-mail: luomeifen@whu.edu.cn.
[1] Zhang M, Luo M, Nie R, Zhang Y. Dataset.xls. Mobile Health User Behavior Survey Data.

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Note: Figure translations are in progress. See original paper for figures.