International Journal of Medical Informatics 172 (2023) 105000

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

A fuzzy-set qualitative comparative analysis exploration of multiple paths to users' continuous use behavior of diabetes self-management apps

Chenchen Gao [a,1], Yucong Shen [a,1], Wenxian Xu [a], Yongjie Zhang [a], Qiongyao Tu [b], Xingjie Zhu [c], Zhongqiu Lu [d,2], Yeqin Yang [a,2]

[a] *School of Nursing, Wenzhou Medical University, Wenzhou, Zhejiang, China*
[b] *Department of Intensive Care Medicine, Huangyan Hospital,Wenzhou Medical University, Taizhou, Zhejiang, China*
[c] *Department of Theater, The First Affiliated Hospital of Wenzhou Medical University, Wenzhou, Zhejiang, China*
[d] *Department of Emergency, The First Affiliated Hospital of Wenzhou Medical University, Wenzhou, Zhejiang, China*

ARTICLE INFO

Keywords:
Continuous use behavior
Diabetes self-management applications
Fuzzy-set qualitative comparative analysis
Information ecologies

ABSTRACT

Background: Despite the obvious potential benefits of diabetes self-management apps, users' continuous use of diabetes self-management apps is still not widespread. Influential factors coexisted in information ecologies are likely to have a synthetic effect on users' continuous use behavior. However, it is less clear how factors in information ecologies combine to influence users' continuous use behavior.
Objective: The objectives of this study are to explore combinations of factors (perceived severity, information quality, service quality, system quality, and social influence) in information ecologies that lead to users' continuous use behavior of diabetes self-management apps and which combination is the most important.
Methods: Purpose sampling was used to recruit diabetes self-management app users from July 1, 2021 to January 31, 2022. Fuzzy-set qualitative comparative analysis (fsQCA) was then employed by conducting necessity and sufficiency analysis.
Results: In total 280 diabetes self-management app users participated. The necessity analysis indicated that no single factor was necessary to cause users' continuous use behavior, and the sufficiency analysis identified five different combinations of factors that lead to users' continuous use behavior. Of these five, the combination of high information quality, high service quality, and high social influence was found to be the most important path.
Conclusions: Users' continuous use behavior of diabetes self-management apps results from the synergistic effects of factors in information ecologies. The five paths that directly contribute to users' continuous use, as well as the four user types preliminarily identified in this study may provide a reference for healthcare providers and app developers.

1. Introduction

Diabetes self-management applications (apps) have been recognized as an effective adjuvant intervention to help patients manage their diabetes, especially during COVID-19 lockdowns [1]. Users' continuous use behavior is a prerequisite for the full effectiveness of these apps [2]. Despite the extensive choice and obvious benefits of diabetes self-management apps, their continuous use is still not widespread in China [3,4]. After patients adopt a diabetes self-management app, 70% of them abandon it quickly [3,4]. This low retention rate reduces patients' exposure to intervention and squeezes the profits of app developers [5,6]. Numerous studies have found that patients who used diabetes self-management apps for only one month have poorer HbA1c improvement than those who use such apps for at least one year [5]. Due to their low retention rate, additional revenue incurred from app usage drops after the first month, and most diabetes self-management apps stop updating quite early [7], leaving many patients without the benefits of up-to-date apps. Thus, understanding influential factors of users' continuous use behavior is a pressing concern worth to be explored.

Information ecology theory provides a comprehensive perspective

E-mail addresses: lzq640814@163.com (Z. Lu), yangyq@wmu.edu.cn (Y. Yang).
[1] These two authors are the co-first authors, they contributed equally.
[2] These two authors are the co-corresponding authors, they contributed equally.

https://doi.org/10.1016/j.ijmedinf.2023.105000
Received 6 September 2022; Received in revised form 10 January 2023; Accepted 14 January 2023
Available online 20 January 2023
1386-5056/

with which to explore multiple influential factors [8,9]. Nardi and O'Day (1999) first proposed the concept of information ecology and introduced it as a diverse, complex, and dynamic system of people, practices, technologies, and values [9]. Wang fleshed out this theory and proposed that information ecologies include "user-specific", "information-specific", "technology-specific", and "environment-specific" dimensions [8]. In this view, numerous studies have searched for the most influential factors of health app users' continuous use behavior within the context of information ecologies [10]. In the user-specific dimension, which refers to individual persons who use the information technology [9], most studies have explored the significance of perceived severity [11,12]; in the information-specific dimension, which refers to the information content and interaction generated through the practice in information ecologies [9], existing studies have focused on factors of information quality and service quality [13-15]; in the technology-specific dimension, which refers to the information technology tools for implementing practice [9], system quality is the most prominent and widely explored factors [14,16]; and in the environment-specific dimension, which refers to the social environment that users are immersed in [9], social influence is the factor constantly mentioned by scholars [17-19]. These existing research has mostly concentrated on net effects, using regression analysis or structural equation modeling (SEM) to estimate each factor's separate impact on health-related app use [20,21]. However, existing results have suggested that factors that coexist in these four dimensions of information ecologies are likely to have a synergistic effect and that no single factor can lead directly to users' continuous use behavior [2,5,10]. Since the causal interactions are complex, merely assessing the net effects, to some extent, may lead to erroneous results that disguise the complex realities of users' continuous use behavior [10,22]. Identifying causal combinations that lead to users' continuous use behavior can be more apposite the complex realities. Besides, different users may have different characteristics of app usage [23], and clarifying causal combinations can help identify user classifications and inform the optimal intervention or personalized design for specific users. Additionally, priorities should be set for intervention strategies [24]. Identifying which combination of factors influences users' continuous use behavior most can help inform the most efficient intervention, develop the priority app development strategy, and finally, improve users' continuous use behavior effectively. Thus, we pose the following questions.

What combinations of perceived severity (user-specific dimension), information quality (information-specific dimension), service quality (information-specific dimension), system quality (technology-specific dimension), and social influence (environment-specific dimension) in the context of information ecologies can lead to users' continuous use behavior of diabetes self-management apps? And which combination is the most important? Thus, the aims of this study are to explore combinations of factors in four dimensions of information ecologies that lead to the continuous use of diabetes self-management apps and clarify the most important combination. To achieve the aims, fuzzy-set qualitative comparative analysis (fsQCA) was employed.

The fsQCA is an emerging statistical tool that is suitable for identifying combinations of causal conditions that lead to an outcome [25]. This technique provides an alternative to conventional quantitative approaches, such as regression analysis and SEM [25]. There are several characteristics that can illustrate the differences between fsQCA and other analytic approaches. First, the idea that each single cause has its own separate, independent impact on an outcome is abandoned and replaced by the assumption that there is "conjuncture causality" among factors. Several causes can be present simultaneously, constituting a "causal combination", for an outcome to occur [26]. Second, fsQCA uses the concept of the "equifinality" of causal combinations, meaning several different combinations of conditions can produce the same outcome [26]. Thus, a given causal combination might not be the only path to a specific outcome. Third, fsQCA assumes "causal asymmetry", meaning that combinations leading to both the presence and absence of an outcome, may not be exactly opposed [25,26].

Based on the characteristics mentioned above, fsQCA assumes that causal conditions are context-specific and conjuncture-specific, and helps modelers not to focus on one single specific causal model that best fits the data, as is typically done with conventional quantitative statistical methods [26]. Instead, fsQCA is used to determine the number and characteristics of different causal models that exist in comparable cases [26].

The fsQCA technique is based on both "case-oriented" and "variable-oriented" approaches, enabling us to take both "qualitative" and "quantitative" into account. This method considers each individual case as a complex combination of properties, views from a holistic perspective, and breaks it down into "a series of features" that include several antecedent conditions and an outcome condition. Then, fsQCA uses the "qualitative" label to characterize included cases and specific "quantitative" operations and algorithms (fuzzy set theoretic analytics and Boolean algebra) to transform each case into numbers [26]. This entire process is similar to a quantitatively statistical approach and offers a formalized and replicable analysis process. Moreover, fsQCA has been widely acknowledged and has shown promise in complex problems in public health behavior research [20,27].

The remainder of the paper is structured as follows. Following this introduction, the theoretical framework and a literature review are presented, as are conceptual models and a hypothesis. Next, the methods used to conduct the analysis are described in detail. The results of the study are then presented. Finally, our conclusions together with limitations and implications are discussed.

2. Theoretical framework and literature review

2.1. Information ecology theory

Information ecology theory provides a theoretical framework with which to explore multiple combinations of influential factors [8,9]. As information ecology theory declared, information users used information technologies as means to obtain specific information [9]. In this view, transmission and feedback activities constantly occur to achieve balance between different information ecologies [8]. Wang highlighted that dimensions of information ecologies have strong interrelationships and dependencies [9]. As Nardi and O'Day suggested, the whole process in which diabetes patients continue using apps to manage their diabetes can be viewed as a complete information ecology [9]. Diabetes patients utilize diabetes self-management app systems to achieve personalized information and services. During this process, transmission and feedback activities among *users* (diabetes patients), *technologies* (functions and equipment of diabetes self-management apps), *information* (information and services provided by apps), and *environment* (the social environment patients are immersed in) are constantly occurring. Previous studies have primarily explored influential factors of health-related apps' continuous use from a limited number of dimensions in information ecologies [28]. Therefore, our novel approach of considering four dimensions based on information ecology theory can better help us to understand potential factors and how they combine systematically.

2.2. Influential factors of the continuous use of health-related apps

2.2.1. The user-specific dimension

The user-specific dimension refers to the individuals who produce, transmit, consume and decompose information [8]. Perceived severity, a core element from protective motivation theory (PMT), has been widely confirmed to influence users' continuous use of health-related apps [29]. In our study, perceived severity is defined as diabetes patients' perception of the degree of seriousness of diabetes, including the clinical and social consequence of diabetes [19,30]. Perceived severity, in essence, belongs to psychological factors of diabetes individuals and can be included in the user-specific dimension. PMT holds that a person's decision on whether or not to take a health-related action is associated with the perceived severity of the disease [30]. Prior studies have found that users with a higher perceived severity level tend to continue using health-related apps [16,31].

2.2.2. The information-specific dimension

The information-specific dimension refers to the information provided or generated by the interaction process of an individual with the system [8]. Notably, the information here is in a broad sense, includes both tangible information content and intangible information interaction [32]. Extant research in the area of health-related app usage has mostly focused on information and service quality in this dimension [33-36], which are two core elements in the information system success (ISS) model [37]. In the context of this paper, information quality related to information content, is defined as the accuracy, currency, completeness, relevance, and readiness of the information content provided by diabetes self-management apps [21,38]. Service quality related to information interaction, is defined as the timeliness, professionalism, continuity, and individualization of services provided by diabetes self-management apps [21,38,39]. Moreover, the service also can be conceptualized as information, as the typical characteristic of a service is converting data to information [40,41]. Thus, information quality and service quality can be included in the information-specific dimension. Diabetes patients have been reported to declare that qualified information and personalized recommendation services matching their needs influence their decision to use apps continually to a large extent [4,42]. Prior research has also advocated that information and service quality are two elements that cannot be ignored in information system continuance [28,36].

2.2.3. The technology-specific dimension

The technology-specific dimension refers to the function and equipment of the technology [8]. Specific to health-related apps, most existing studies mentioned system quality, another core element of the ISS model [14,21,37]. In the context of this paper, system quality is defined as the functional qualities of diabetes self-management apps, including convenience, trustworthiness, flexibility, diversity, and responsiveness [21,37]. According to its definition, system quality is related to apps' functional qualities, and should be included in the technology-specific dimension. Previous research has found mixed effects on system quality. Some studies have indicated that patients pay more attention to information quality and less to system quality [34], but others have purported that the system quality of health-related apps significantly influences users' experiences and continuous use [43,44].

2.2.4. The environment-specific dimension

The environment-specific dimension refers to the overall environment in a society composed of individuals or groups and their communication activities [8,45]. Social influence is a generally assessed factor in health-related apps' continuous usage in this dimension [46,47]. In our study, social influence is defined as the changes in diabetes patients' behaviors that arise from interactions with important others, such as healthcare professionals, relatives, families, and friends [47,48]. Social influence is related to interactions among people in the social environment, and thus can be included in the environment-specific dimension. Prior studies have found that patients are very concerned about the opinions of their friends, relatives, families, and healthcare professionals toward health-related apps [49]. If these people encouraged users to continue using such apps, their determination to keep using them would be likely to increase greatly [49].

3. Conceptual model

We now construct several conceptual models (see Fig. 1) based on the strategies recommended by fsQCA [26]. In the first strategy we consider any possible factors in health-related app use and their significance. Several systematic reviews and meta-analyses of health app use have already summarized these influential factors in the existing research [28]. After a literature review of the framework of information ecologies, we preliminary chose perceived severity, information quality, service quality, system quality, and social influence as five core influential factors of continuous use behaviors.

In the second strategy we consider theory perspective. The fsQCA suggested the integration of different factors from two or three theories [26], because the continuous use behavior of diabetes self-management apps is a phenomenon that involves both information system continuance and healthcare guidance. Thus, we took the ISS model, a classical theory of information systems continuance into account. The ISS model has three core elements: information quality, service quality, and system quality [21], and these are also included in our model in the first strategy as mentioned above. In addition to considering traditional theories from information system continuance, theories applicable to healthcare contexts specifically were also considered.

The ability of PMT, with its core element of perceived severity [30], and its applicability to healthcare has been well recognized in health informatics research [16,29]. Diabetes is a chronic disease that requires long-term self-management, and patients' awareness of this fact may

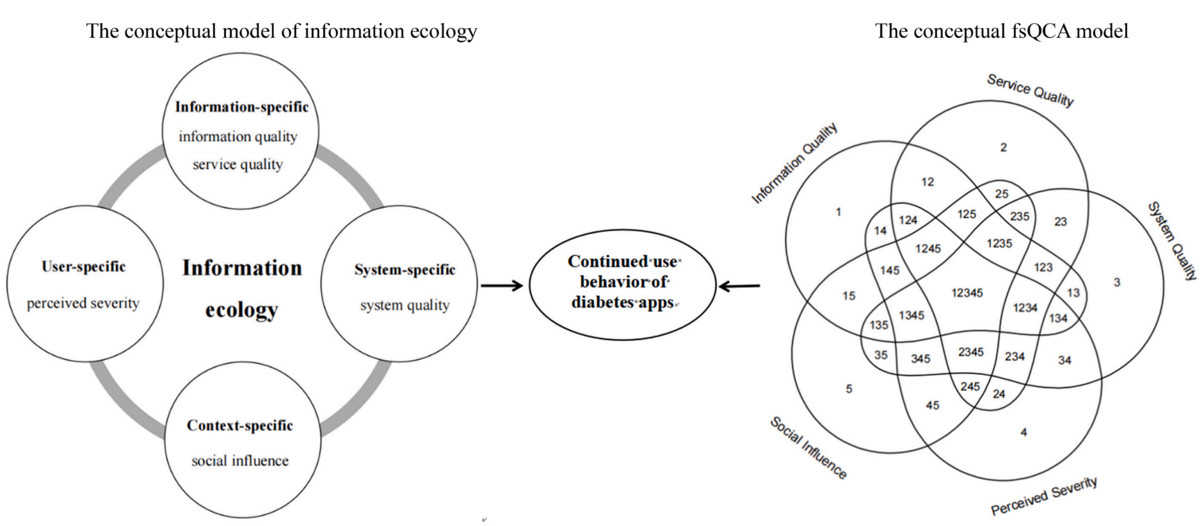

Fig. 1. Note: "1″ refers to information quality; "2" refers to service quality; "3" refers to system quality; "4" refers to perceived severity; and "5" refers to social influence; the intersecting parts refer to combinations of these conditions.

influence their health behavior. Thus, we adopted perceived severity into the model.

The third strategy from fsQCA recommended keeping the number of factors quite low [26]. As the numbers of factors increases, the number of possible combinations of these conditions increases exponentially [26], and the fsQCA recommended that the number of conditions should be in the range of 4 to 7 and that the corresponding samples were considered optimal for fsQCA [26]. Thus, based on the above two strategies, we considered the minimum number of antecedent conditions in each dimension of information ecology. The user-specific dimension included perceived severity; the information-specific dimension included information and service quality; the technology-specific dimension included system quality; and the environment-specific dimension included social influence. We included these five factors in our fsQCA model as antecedent conditions and included continued use behavior as the outcome condition, making six conditions total. We offer the following hypothesis.

Hypothesis 1. *The five conditions of perceived severity, information quality, service quality, system quality, social influence in information ecologies combined into different paths lead to the continuous use behavior of diabetes self-management apps.*

4. Methodology

4.1. Survey development

We developed a structured questionnaire consisting of two parts in order to test our hypothesis. Part A contains the demographic information of participants, including their gender, age, type of diabetes, diabetes self-management app usage experience, the name of the used diabetes self-management app, and app usage duration. Part B contains six constructs (see Appendix A): perceived severity (3 items), information quality (6 items), service quality (5 items), system quality (4 items), social influence (3 items), and continuous use behavior (3 items). Each item was adapted from existing scales and was measured on a five-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). Additionally, every item was validated in previous studies. We performed confirmatory factor analysis (CFA), based on a partial least squares structural equation model (PLS-SEM), using SmartPLS 3 software to test the instrument's reliability and validity. The Cronbach's alpha value, indicator loading, and composite reliability (CR) were employed as well to evaluate the instrument's reliability [50].

The validity of the survey was evaluated with content validity, convergent validity, and discriminant validity [51]. Content validity was assessed according to the second round of an expert consultation, in which we invited a pool of 12 experts in medical informatics (n=4), gerontology (n=3), endocrinology (n=4), and psychology (n=1) to evaluate the correlation between the items and corresponding dimensions. Content validity was assessed using the item-level content validity index (I-CVI) and the average scale-level content validity index (S-CVI/Ave) [52]. The I-CVI was calculated as the number of experts who awarded a rating of 4 or 5 for a particular item divided by the total number of experts, and S-CVI/Ave was the average of all I-CVIs [52]. After consulting the experts, a pilot test of thirty diabetes self-management app users was administered to evaluate the readability and semantic clarity of each item. Convergent validity was then assessed with the estimates of average variance extracted (AVE) [53]. Finally we used the Fornell–Larcker criterion to evaluate the discriminant validity of the survey instrument [53].

4.2. Sample data

The necessary sample size needed for fsQCA is highly associated with the number of conditions included. To achieve the best results with fsQCA, the sample size should be at least 2^k, where k is the number of conditions [25,54]. If the sample size cannot not reach 2^k, problems of limited diversity, theoretical interpretation, and validity arise [55]. Since six conditions were used in this study, the sample size must be at least 2^6, namely 64 [26].

To select our sample of participants, we used purpose sampling to recruit participants from July 1, 2021 to January 31, 2022 from the 1st Affiliated Hospital of Wenzhou Medical University. This hospital has the largest source of patients using diabetes self-management apps in Wenzhou, China and cares for both urban and rural patients. A researcher attended the diabetes clinic and in-patient department to invite patients who were (1) diagnosed with type 1 or type 2 diabetes; (2) had used diabetes self-management apps to any degree; (3) were over 18 years old; and (4) volunteered to participate. The sampling strategies used were maximum difference sampling and snowball sampling. To improve the diversity of cases [26], maximum difference sampling was used to reach more participants of different genders, ages, types of diabetes, and degrees of diabetes self-management app usage.

Since our data was collected during COVID-19 lockdowns in China, where most diabetes patients were kept at home, and thus we used an online platform to connect with study participants, and snowball sampling was used to approach online participants. Offline participants offered the recruiting researcher their contact information and in some cases that of other eligible patients who were at home or in the community at large. An online version of the questionnaire was distributed through the web-based survey platform, WenJuanXing. Each participant was allowed to submit only once, and we screened for this using IP addresses. The Human Research Ethics Committee of the 1st Affiliated Hospital of Wenzhou Medical University approved this study (approval number: 2021-zx-012).

4.3. Data analysis of fsQCA

We used fsQCA software (version 3.0) to conduct our analysis [56]. First, each survey response was viewed as a case, which were supposed to be qualitatively characterized by the continuous use of diabetes self-management app users. Second, each case was broken down into a series of causal combinations based on the results of our structured questionnaire. Third, we converted the questionnaire data from the original five-point Likert scale into a dataset to conduct calibration by identifying three points: full membership, full nonmembership, and a cross-over point [20,27,57]. Based on the recommendation of Ragin [26], the threshold for full membership threshold was identified as the 95th percentile, the crossover point was identified as the median, and the full nonmembership point was identified as the 5th percentile. The calibration values for each variable are shown in Table 1. Fourth, we conducted necessity analysis of all variables and their negations. Any causal attribute with a consistency greater than 0.90 and coverage greater than 0.50 was considered to be necessary condition [58]. Fifth we conducted sufficiency analysis by creating a truth table with all logically possible combinations of causal conditions associated with users' continuous use behavior. The truth table was created according to the following criteria: (1) each cell had to have at least one case, (2) each cell had to have a consistency score of 0.8, and (3) each cell had to have a proportional reduction inconsistency (PRI) level of 0.65. Finally, we implemented the

Table 1
Variables and calibration values (n = 280).

Abbreviations of variables	Variables	95 % percentile	Median	5 % percentile
PS	Perceived severity	5.00	4.67	3.33
IQ	Information quality	5.00	4.00	3.00
SEQ	Service quality	5.00	3.40	2.00
SYQ	System quality	5.00	4.00	3.00
SI	Social influence	5.00	4.00	2.50
CUB	Continuous use behavior	5.00	4.17	1.00

Table 2
Demographic information (sample size = 280).

Characteristics	Frequency (n)	Percentage (%)
Gender		
Male	147	52.5 %
Female	133	47.5 %
Type of diabetes		
Type 1 diabetes	118	42.1 %
Type 2 diabetes	162	57.9 %
Age		
18 ~ 24 years	44	15.7 %
25 ~ 34 years	95	33.9 %
35 ~ 44 years	78	27.9 %
45 ~ 54 years	43	15.4 %
55 ~ 64 years	10	3.6 %
>=65 years	10	3.6 %
Types of diabetes apps		
Dnurse	20	7.1 %
MMC butler	106	37.9 %
Tangtang Quan	116	41.1 %
Others	38	13.5 %
Diabetes apps usage duration		
<=1 month	41	14.6 %
>1 month, <=3 months	30	10.7 %
>3 months, <=6 months	19	6.8 %
>6 months, <=9months	4	1.4 %
>9 months	186	66.4 %

Quine-McCluskey algorithm to reduce numerous complex causal conditions into a simplified set of pathways. This step also distinguished core attributes and peripheral attributes of conditions in each solution. Core attributes indicated a strong causal relationship between the antecedent condition and the outcome, while peripheral attributes indicated a weaker causal relationship.

5. Results

5.1. Sample characteristics

A total of 293 questionnaires were distributed with a 100% response rate. Among them, we deemed 13 questionnaires to be invalid because the participants marked 5-points for each item. Thus, a total of 280 participants (121 offline, 159 online) who completed the structured questionnaire were included in the sample, and the minimum size requirement was met. Interestingly, 77.2% of the participants were between 24 and 54 years of age. Detailed demographic information is shown in Table 2.

5.2. Survey reliability and validity

Before performing the fsQCA, we measured the reliability and validity of the survey instrument we used. The Cronbach's alpha and composite reliability of the six constructs ranged from 0.801 to 0.931, and 0.880 to 0.947, respectively. All Cronbach's alpha and composite reliability scores exceeded 0.7, showing good reliability [59]. The indicator loadings of each item ranged from 0.716 to 0.939 in their respective dimensions, greater than the criteria of 0.6, indicating practical significance [53]. Furthermore, the I-CVI of each item ranged from 0.83 to 1.00, and the S-CVI/Ave of the questionnaire was 0.93, which both exceeded the recommended value (I-CVI>0.78, S-CVI/Ave≥0.90) [52], suggesting good content validity. In addition, the AVE values of all constructs ranged from 0.627 to 0.767, exceeding the minimum threshold of 0.50 as suggested by Hair [53] and indicating good convergent validity [60]. Finally, the square root of each factor's average variance extracted (AVE) was larger than its correlations with other factors, suggesting good discriminant validity [53]. Appendix A lists the items used to measure each construct, along with the source, the results of indicator loadings, Cronbach's alpha, CR, and AVE. Appendix B displays the results for discriminant validity.

Table 3
Necessity testing results.

Conditions	Continuous use behavior	
	Consistency	Coverage
Perceived severity	0.636425	0.683230
~Perceived severity	0.527619	0.662354
Information quality	0.631179	0.756435
~Information quality	0.601481	0.673052
Service quality	0.638955	0.717861
~Service quality	0.564525	0.673664
System quality	0.568290	0.722933
~System quality	0.657236	0.697714
Social influence	0.544282	0.730594
~Social influence	0.684442	0.696215

Note: "~" refers to negation of the condition.

5.3. fsQCA results

5.3.1. Necessity analysis

We calculated consistency scores for each single factor as a superset of continuous use behavior outcomes (see Table 3). The consistency value of each condition and its negation ranged from 0.523 to 0.684, not exceeding the recommended value 0.80 [61]. This suggests that no single factor is necessary for users' continuous use behavior.

5.3.2. Sufficiency analysis

Following previous studies, we conducted sufficiency analysis by creating a truth table [25,62]. Five different solutions contributing to users' continuous use behavior of diabetes self-management apps and four user types were thusly identified (see Table 4). The overall solution consistency was 0.833, and overall solution coverage was 0.643. These two values reached the recommended threshold values of 0.8 and 0.45, respectively. The consistency scores of each solution ranged from 0.882 to 0.912, exceeding the recommended threshold values of 0.85. These indicate that the data adjusted well to all factors combinations [25,63]. Our detailed interpretation of the five solutions is enumerated below.

1. Solution 1 was high information quality AND low system quality. The raw coverage value was 0.430, indicating that 43.0% of users continued to use diabetes apps that had high information quality and low system quality. We thus roughly labeled these users as "information-oriented users".
2. Solution 2 was low perceived severity AND high information quality AND high service quality. The raw coverage value was 0.314, showing that 31.4% of users, who had a lower level of perceived severity, kept using diabetes apps with high-quality information and services. In contrast to users in solution 1 (high information quality AND low system quality), this user type wasn't satisfied with simply getting information; these users also wanted to obtain service support, such as online consultations, to solve their problems. We labeled these users as "problem-solving users".
3. Solution 3 was high information quality AND high service quality AND high social influence. The raw coverage value was 0.443, showing that 44.3% of users continually to used diabetes apps in this path. Unlike other solutions, these users were more externally motivated to continue using diabetes apps. High information and service quality were not enough to capture their usage. A high amount of social influence, including professional and nonprofessional support alike toward the diabetes app, was also an important factor for them to continue using it. We labeled these users as "externally-motivated users".
4. Solution 4 was high perceived severity AND high information quality AND low service quality AND low social influence. The raw coverage value was 0.286, indicating that 28.6% of diabetes app users, who

had a high level of severity perception, valued information quality as well. They did not have such high requirements for social influence or service quality. They were more driven to continue using the diabetes app for their own internal reasons.

5. Solution 5 was high perceived severity AND low information quality AND high service quality AND low social influence. The raw coverage value for this factor combination was 0.305, indicating that 30.5% of diabetes app continuous users who had a high level of severity perception also valued service quality. As we can see, this solution was nearly identical to the solution 4 (high perceived severity AND high information quality AND low service quality AND low social influence); the only difference lay in the information quality and service quality. Given this, we collectively labeled solution 4 and 5 users as “self-driven users”.

Following Ragin [61] and previous studies [27,64], this study compared the raw coverage values of these five solutions to identify the most important path contributing to users’ continuous use behavior of diabetes apps. The result indicated that Solution 3: high information quality AND high service quality AND high social influence, was the most important path as it had the highest raw coverage value of 0.443. It means that 44.3% of diabetes app users continue to use the diabetes app because it provides them with high-quality information, services, and high social influence simultaneously.

5.3.3. Robustness tests

The fsQCA also involved changing the points of calibration, case frequency thresholds, and consistency threshold to perform the robustness tests [25,65]. To this end, two assessment indices were used to evaluate the test [65]. The first assessment index was the result of solution terms. If there was a clear subset relation between different results of solution terms, then the results could be interpreted as robust, even if these solution terms looked different on the surface [65]. The second assessment index was the values of overall solution consistency and coverage. If differences in consistency and coverage were roughly the same, then the results could be considered robust [65]. We describe the operations and results of the robustness tests in detail below.

To reiterate, (1) the three points (full membership, full nonmembership, cross-over point) of calibration in this study were the 95th, 5th, and median, respectively. We changed these to the 90th, 10th, and median, respectively, to conduct the first robustness test; (2) The case frequency threshold in this study was “1”. We changed this from “1” to “2” to conduct the second robustness test. This means that only a row in the truth table with at least 2 cases could be included in the sufficiency analysis; (3) The consistency threshold of this study was the recommended value of 0.8. We changed it from “0.8” to “0.85” to conduct the third robustness test. This change means only the rows in the truth table with a consistency score over 0.85 could be included in the sufficiency analysis.

The detailed results of the assessment indices are displayed in Table 5. The first assessment index is the solution terms. After changing the case frequency threshold and consistency threshold, five solution terms were still present, and they did not change. For the change in the three points of calibration, the solution 4 was absent. However, the others remained and did not change. The solution terms after changing were a subset of the original solution terms, and thus we consider the original solutions we found to be robust. The second assessment index was the overall solution consistency and coverage. The original overall solution consistency and coverage were 0.645 and 0.837, respectively. Hence, the overall solution consistency and coverage in the three-time changes were all highly consistent with the original value, indicating

Table 4
Multiple paths to diabetes app users’ continuous use behavior.

Configuration	Solutions				
	Information-oriented users	Problem-solving users	Externally-motivated users	Self-driven users	
	1	2	3	4	5
Perceived severity (PS)		⊗		●	●
Information quality (IQ)	●	●	●	●	⊗
Service quality (SEQ)		●	●	⊗	●
System quality (SYQ)	⊗				
Social influence (SI)			●	⊗	⊗
Consistency	0.882	0.883	0.853	0.912	0.892
Raw coverage	0.430	0.315	0.445	0.287	0.305
Unique coverage	0.037	0.012	0.068	0.016	0.052
Overall solution coverage	0.645				
Overall solution consistency	0.837				

Note: All factors are core attributes; “●” refers to presence of the condition; “⊗” refers to negation of the condition; blank spaces denote that the condition may be either present or absent.

Table 5
Robustness test results.

The original solution terms	(1) Changed thresholds form 95th, 5th to 90th, 10th	(2) Changed case frequency thresholds from at least 1 to 2 cases	(3) Changed the consistency score from 0.8 to 0.85
Solution 1: IQ*~SYQ	✔	✔	✔
Solution 2: ~PS*IQ*SEQ	✔	✔	✔
Solution 3: IQ*SEQ*SI	✔	✔	✔
Solution 4: PS*IQ*~SEQ*~SI		✔	✔
Solution 5: PS*~IQ*SEQ*~SI	✔	✔	✔
Overall solution coverage: 0.645	0.609	0.632	0.634
Overall solution consistency: 0.837	0.833	0.837	0.833

Note: ✔means the solution exists; blank spaces mean the solution does not exist.

robustness of the original solutions.

6. Discussion

This study proposes that no single factor in information ecologies could directly lead to users' continuous use. More specifically, this study elucidates perceived severity, information quality, system quality, service quality, and social influence combined into five different combinations to synergistically achieve users' continuous use behavior of diabetes self-management apps to varying degrees. The results confirm prior research that factors coexist in information ecologies cooperation and interaction [8-10], and the five combinations we identified constitute novel findings on apps' continuous behavior.

The solution 3 (high information quality AND high service quality AND high social influence) is the most important path to users' continuous use behavior of diabetes self-management apps. Here, information-specific (information quality and service quality) and environment-specific dimension factors (social influence) working together drove a prominent part of users to maintain their app use continually. Prior research has only revealed net effects of social influence, information quality, and service quality [28,66], but in this study we have identified synergistic effects for these factors as well. Moreover, the solution 2 (high information quality AND high service quality AND low perceived severity) and solution 3 (high information quality AND high service quality AND high social influence) demonstrate that even for apps that provide high-quality information or/and services, users still need some internal (for example, perceived severity) or external (for example, social influence) factors in order to maintain their usage. As prior studies [16,19] and health belief models have [67] noted, the level of severity perception gives patients the energy to act, and external factors such as interpersonal interactions become stimuli to trigger this behavior continually. This finding also provides evidence that factors in information ecologies combined and had synergistic effects in influencing app use.

The information-specific dimension is the most prominent dimension, as all paths contained at least high information quality or high service quality. This agrees with prior findings that the information and service patients receive from health apps have important effects on their continuous use [68]. This also suggests that diabetes self-management apps play the dual role of "information provider" (presenting a diabetes-related information product) and "service provider" (offering diabetes-related support to patients). More importantly, expanding existing findings on the individual effects of information quality and service quality, we find a significant synergistic effect of information quality and service quality as this combination was present in four out of five paths. This finding emphasizes the importance of integrating information and service quality, which has been mentioned in prior studies as well [21,68]. Thus, under the information-specific dimension, the coexistence of information quality and service quality can meet users' informational needs to the greatest extent. Hence, simultaneously ensuring information and service quality may be a promising strategy for diabetes self-management apps in maintaining their users.

The system quality does not appear to be an important component of continuous use behavior, as system quality was only present in the solution 1 (high information quality AND low system quality) and was not present in solution 2–5. Consistent with prior works [49,68,69], this result implies that technology-specific factors are relatively weak in information ecologies. Users in solution 2–5, where system quality was not present, continued using diabetes apps regardless of good or bad system quality. In solution 1 (high information quality AND low system quality), even information-oriented users tolerated poor systems as long as diabetes self-management apps ensured high-quality information. This result is unexpected but reasonable. Most existing diabetes self-management apps offer similar functionalities and combine only one to two functions in one app [70]. Few diabetes apps in China provide a comprehensive set of tools for self-management [71]. Users may thus become indifferent to system quality after trying several apps with highly homogeneous functions [69].

6.1. Theoretical implications

The results of our study have some theoretical implications. First, we find that no single factor was necessary for users' continuous use, instead finding that information system usage results from synergistic effects as opposed to net effects of factors. Second, from the fsQCA analysis, we identify five paths that contribute to users' continuous use of diabetes self-management apps, extending the growing discussion on how multiple conditions spur continuous usage [20,64]. Third, we adopt information ecology theory as a main theoretical foundation and explored potential factors under its four dimensions. Prior studies have often explored these factors from only one or two dimensions and considered their net effects from a separation perspective [28]. In contrast to this, our current study illustrates how health-related information system continuance research can be incrementally advanced in a meaningful manner. We suggest that future research explore factors of continuous use behaviors from the perspective of information ecologies, and try to analyze their combinations among user-, information-, technology-, and environment-specific dimensions in even greater depth. Fourth, based on our framework of information ecologies, three core factors are merged from the ISS model to explain users' continuous usage behaviors. Some have argued that it may be a misapplication to employ constructs of adoption theories (such as the Technology Acceptance Model) for information system continuance because there are differences between adoption and continuous use behaviors [72]. We suggest that future research therefore concentrate on the continuance theory to explain continuance usage behaviors.

6.2. Practical implications

The findings of this study can be employed by healthcare providers and app developers to streamline their intervention strategies. This study analyzed five paths systematically and put forward suggestions to increase diabetes self-management apps users' continuous use. Based on the characteristics of five paths, this study preliminarily labelled four different user types, who presented a variety of perceptions and preferences. This provides an opportunity for more advanced user profiling by developers in the future. Healthcare providers can inform the optimal intervention for each user according to the user classifications.

This study declared the most important paths to continuous usage: high information quality, high service quality, and high social influence. To meet the majority of users' usage preference, healthcare providers and app developers should ensure apps' information and service quality, as well as improve social influence. In the real-world context it is challenging for app developers to simultaneously optimize all four dimensions of in diabetes apps. Thus, we suggest that diabetes self-management apps treat information quality and service quality as their primary objectives. Diabetes apps can even integrate artificial intelligence technologies to ensure both high information and high service quality. Meanwhile, they may be able to improve social influence through advertising, expert publicity, and family-centered health education projects [24].

The results of this study also acknowledged the significant influence of high perceived severity, since this factor were present in solution 4 and solution 5. If only one of information or service quality could be guaranteed, and the social influence factor were weak at the same time, stimulating user' perceived severity of diabetes was one path to continuous use. App designers and healthcare providers should therefore strive to induce and maintain patients' awareness of the severity of diabetes.

6.3. Limitations and directions for future research

As with any empirical study, this study has its limitations. First, the sample consists of mostly young and middle-aged adults, and this may limit the generalization of our findings to the elderly. Nevertheless, this may be due to the fact that few elderly patients actually use diabetes apps [73]. Second, this study was based on self-reported data. Future research could integrate other methods such as depth interviews and observations to provide a complementary picture to our findings. Third, despite the numeric advantage of using fsQCA, we acknowledge that this method limits the number of included factors. If further studies want to explore combinations of more factors, the sample size also needs to be increased by commensurate powers of 2 [25], and the results would become much more complex [54] as well. For this reason, we only included six factors.

Future research should explore more combinations of other factors under an expanding sample, such as habits, hedonism, and trust, to enrich our findings. For the same reason, despite information quality, service quality, and system quality being multidimensional [21], we only examined them from an overall perspective. Future research should examine the multidimensional aspects of these factors to gain insights of greater detail.

7. Conclusion

In information ecologies, factors of information-specific, user-specific, environment-specific, and technology-specific dimensions cooperate to form five different paths that contribute to users' continuous use behavior of diabetes self-management apps. The configuration of high information quality, high service quality, and high social influence had the greatest influence on diabetes patients' continuous app usage, and the information-specific dimension was the most prominent dimension. Furthermore, we systematically integrate the five paths to put forward suggestions for healthcare providers and app developers for streamlining their intervention strategies. Importantly, the four user types that we preliminary identified may also provide an opportunity for more advanced user profiling in the future.

CRediT authorship contribution statement

Chenchen Gao: Writing – original draft, Writing – review & editing. **Yucong Shen:** Data curation, Writing – original draft, Writing – review & editing. **Wenxian Xu:** Statistical analysis. **Yongjie Zhang:** Statistical analysis. **Qiongyao Tu:** Data curation. **Xingjie Zhu:** Data curation. **Zhongqiu Lu:** Conceptualization, Supervision, Writing – review & editing. **Yeqin Yang:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by Nature science foundation of Zhejiang Province (LQ21G030017) and Zhejiang Office of Philsophy and Social Science (22NDQN253YB).

Appendix A. . Instrument reliability and validity

Construct	Item	Sources	Factor loading	Cronbach's alpha	CR	AVE
Perceived severity (PS)	PS1. If diabetes is not well controlled, serious complications may occur.	(Li Hui, 2019 [74])	0.897	0.801	0.880	0.712
	PS2. Diabetes can increase the risk of cardiovascular disease.		0.905			
	PS3.Totally, I perceived diabetes as sever.		0.716			
Information quality (IQ)	IQ1. Information provided by this diabetes self-management app is comprehensive.	(Shim M, 2020 [34]; Chen Y, 2018 [13])	0.832	0.883	0.910	0.629
	IQ2. Information provided by this diabetes self-management app is continually updated.		0.797			
	IQ3. Information provided by this diabetes self-management app is clear and short.		0.781			
	IQ4. Information provided by this diabetes self-management app is applicable to the real world.		0.824			
	IQ5.Information provided by this diabetes self-management app is consistent with other sources (doctors, patients, diabetes-related books, etc.)		0.743			
	IQ6. Information provided by this diabetes self-management app is applicable to my diabetes informational needs.		0.778			
Service quality (SEQ)	SEQ1. This diabetes self-management app provides prompt responses to my questions.	(Shim M, 2020 [34]; Asker S, 2013 [75])	0.900	0.931	0.947	0.783
	SEQ2. This diabetes self-management app provides professional services for my diabetes-related questions.		0.918			
	SEQ3. Professionals on this diabetes self-management app provide me with continuing services (such as adjusting insulin dose and drug doses, etc.)		0.888			
	SEQ4. This diabetes self-management app communicates well with me.		0.868			
	SEQ5. Professionals on this diabetes self-management app care about me.		0.849			
System quality (SYQ)	SYQ1. The layout of this diabetes self-management app homepage is clear and concise.	(Guo X,2020 [43]; Shim M 2020 [34])	0.939	0.861	0.882	0.654
	SYQ2. The system of this diabetes self-management app runs smoothly.		0.803			
	SYQ3. This diabetes self-management app has a fast response speed.		0.723			
	SYQ4. Overall, this diabetes self-management app is good.		0.752			
Social influence (SI)	SI1. People who are important to me (friends and family) think that I should continue using diabetes self-management apps.	(Zhang YY, 2019 [19]; Li Hui, 2020 [74])	0.829	0.869	0.908	0.712

(*continued on next page*)

(*continued*)

Construct	Item	Sources	Factor loading	Cronbach's alpha	CR	AVE
	SI2. People whose opinions that I value (doctors, nurses, etc.) prefer that I continue using diabetes self-management apps.		0.898			
	SI3. People who influence my behavior (social media, friend, family, doctors, nurses, etc.) think that I should continue using diabetes self-management apps.		0.862			
Continuous use behavior (CUB)	CUB1. Number of days I currently use the diabetes self-management app per week: 0 | 1–2 | 3–4 | 5–6 | ≥7	(Bhattacherjee, 2008 [76])	0854	0.848	0.908	0.767
	CUB2. Number of minutes I currently use the diabetes self-management app per time: 0 | 1–3 | 4–6 | 7-9 | ≥10		0.901			
	CUB3. Number of the app functions I currently use per time: 0 | 1 | 2 | 3 | ≥ 4		0.873			

Note: **α** = Cronbach's alpha; AVE = average variance extracted; CR = composite reliability.

Appendix B. . Discriminant validity results

Variables	PS	IQ	SEQ	SYQ	SI	CUB
Perceived severity (PS)	0.844					
Information quality (IQ)	0.273	0.793				
Service quality (SEQ)	0.118	0.389	0.885			
System quality (SYQ)	0.235	0.649	0.418	0.798		
Social influence (SI)	0.228	0.445	0.338	0.394	0.844	
Continuous use behavior (CUB)	0.233	0.187	0.269	0.071	0.129	0.876

What was known on the topic

- Users' continuous use behavior is a prerequisite for the full effectiveness of diabetes self-management apps.
- Information system continuance is not resulting from factors' net effects but from synergistic effects of different factors.

What this study has added (Highlight)

- No single factor is necessary for users' continued use behavior of diabetes self-management apps.
- The information-specific dimension containing information quality and service quality is the most important.
- Five paths are identified. Of these five, the combination of high information quality, high service quality, and high social influence was found to be the most important path.
- The five paths that directly contribute to users' continuous use behavior, as well as the four user types preliminary identified in this study may provide a reference for healthcare providers and app developers.

References

[1] M. Banerjee, S. Chakraborty, R. Pal, Diabetes self-management amid COVID-19 pandemic, Diabetes Metabolic Syndrome 14 (4) (2020) 351–354.
[2] D. Biduski, et al., Assessing long-term user experience on a mobile health application through an in-app embedded conversation-based questionnaire, Comput. Hum. Behav. 104 (2020), 106169.
[3] X. Wu, X. Guo, Z. Zhang, The Efficacy of Mobile Phone Apps for Lifestyle Modification in Diabetes: Systematic Review and Meta-Analysis, JMIR Mhealth Uhealth 7 (1) (2019).
[4] D. Katz, N. Dalton, B. Price, *Failing the challenge: Diabetes apps & long-term daily adoption.* 2015.
[5] Y.-Z. Tu, et al., The Effects of Continuous Usage of a Diabetes Management App on Glycemic Control in Real-world Clinical Practice: Retrospective Analysis, J. Med. Internet Res. 23 (7) (2021).
[6] Y. Zhang, et al., Exploration of Users' Perspectives and Needs and Design of a Type 1 Diabetes Management Mobile App: Mixed-Methods Study, JMIR Mhealth Uhealth 6 (9) (2018) e11400.
[7] J. Hsu, et al., The Top Chinese Mobile Health Apps: A Systematic Investigation, J. Med. Internet Res. 18 (8) (2016).
[8] X. Wang, D. Liu, Research of the Elements and Evaluation Index Construction of Enterprise Information Ecological System, Library Inform. Service 54 (16) (2010) 22–25.
[9] B.A. Nardi, V. O'Day, Information ecologies: Using technology with heart, Mit Press, 1999.
[10] Y. Shen, et al., Online health management continuance and the moderating effect of service type and age difference: A meta-analysis, Health Inform. J. 28 (3) (2022).
[11] C. Xie, S. Jia, C. He, An Empirical Study on the Factors Affecting Elderly Users' Continuance Intention of Shared Nurses, Risk Manage. Healthcare Policy 13 (2020) 1849–1860.
[12] J. Li, et al., Users' intention to continue using social fitness-tracking apps: expectation confirmation theory and social comparison theory perspective, Inform. Health Soc. Care 44 (3) (2019) 298–312.
[13] Y. Chen, et al., Central or peripheral? Cognition elaboration cues' effect on users' continuance intention of mobile health applications in the developing markets, Int. J. Med. Inf. 116 (2018) 33–45.
[14] T. Song, et al., Measuring Success of Patients' Continuous Use of Mobile Health Services for Self-management of Chronic Conditions: Model Development and Validation, J. Med. Internet Res. 23 (7) (2021).
[15] A.I. Alzahrani, et al., *Users' intention to continue using mHealth services: A DEMATEL approach during the COVID-19 pandemic.* Technology in society, 2022. **68**: p. 101862-101862.
[16] F.B. Franque, et al., A meta-analysis of the quantitative studies in continuance intention to use an information system, Internet Res. 31 (1) (2021) 123–158.
[17] S.p. Yuan, et al., *Keep Using My Health Apps: Discover Users' Perception of Health and Fitness Apps with the UTAUT2 Model.* Telemedicine journal and e-health : the official journal of the American Telemedicine Association, 2015. **21**(9): p. 735-741.
[18] B. Bai, Z. Guo, Understanding Users' Continuance Usage Behavior Towards Digital Health Information System Driven by the Digital Revolution Under COVID-19 Context: An Extended UTAUT Model, Psychol. Res. Behav. Manag. 15 (2022) 2831–2842.
[19] Y. Zhang, et al., Factors Influencing Patients' Intentions to Use Diabetes Management Apps Based on an Extended Unified Theory of Acceptance and Use of Technology Model: Web-Based Survey, J. Med. Internet Res. 21 (8) (2019) e15023.

[20] S. Fu, et al., Understanding health information literacy of mHealth app users from digital wellbeing perspective: Evidence from regression analysis and fsQCA, Libr. Inf. Sci. Res. 43 (3) (2021), 101108.
[21] W.H. DeLone, E.R. McLean, The DeLone and McLean model of information systems success: a ten-year update, J. Manag. Inf. Syst. 19 (4) (2003) 9–30.
[22] N.F. Richter, et al., When predictors of outcomes are necessary: Guidelines for the combined use of PLS-SEM and NCA, Ind. Manag. Data Syst. (2020).
[23] S. Lockey, et al., Profiling adopters (and non-adopters) of a contact tracing mobile application: insights from Australia, Int. J. Med. Inf. 149 (2021), 104414.
[24] Y.H. Kwan, et al., A systematic review of nudge theories and strategies used to influence adult health behaviour and outcome in diabetes management, Diabetes Metab. 46 (6) (2020) 450–460.
[25] C.C. Ragin, Redesigning social inquiry: Fuzzy sets and beyond, University of Chicago Press, 2009.
[26] B. Rihoux, C.C. Ragin, *Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques (Applied Social Research Methods)*. 2008: Sage Publications.
[27] I.O. Pappas, et al., Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions, J. Bus. Res. 69 (2) (2016) 794–803.
[28] Y. Shen, et al., Online health management continuance and the moderating effect of service type and age difference: A meta-analysis. Health Informatics J, 2022. **28** (3): p. 14604582221119950.
[29] H.-L. Hsieh, et al., A Study of Personal Health Record User's Behavioral Model Based on the PMT and UTAUT Integrative Perspective, Int. J. Environ. Res. Public Health 14 (1) (2017).
[30] R.W. Rogers, A Protection Motivation Theory of Fear Appeals and Attitude Change1, J. Psychol. 91 (1) (1975) 93–114.
[31] É. Maillet, L. Mathieu, C. Sicotte, Modeling factors explaining the acceptance, actual use and satisfaction of nurses using an Electronic Patient Record in acute care settings: An extension of the UTAUT, Int. J. Med. Inf. 84 (1) (2015) 36–47.
[32] B.K. Kahn, D.M. Strong, R.Y. Wang, Information quality benchmarks: product and service performance, Commun. ACM 45 (4) (2002) 184–192.
[33] B. Wu, Patient Continued Use of Online Health Care Communities: Web Mining of Patient-Doctor Communication, J. Med. Internet Res. 20 (4) (2018) e126.
[34] M. Shim, H.S. Jo, What quality factors matter in enhancing the perceived benefits of online health information sites? Application of the updated DeLone and McLean Information Systems Success Model, Int. J. Med. Inf. 137 (2020), 104093.
[35] X. Liu, et al., Using Telemedicine during the COVID-19 Pandemic: How Service Quality Affects Patients' Consultation, Int. J. Environ. Res. Public Health 19 (19) (2022).
[36] Y. Zhang, Y. Kim, Consumers' Evaluation of Web-Based Health Information Quality: Meta-analysis, J. Med. Internet Res. 24 (4) (2022).
[37] D. Mclean, I.S. Success, The DeLone and McLean Model of Information Systems Success: A Ten-Year Update, J. Manag. Inf. Syst. 19 (4) (2003) 9–30.
[38] M. Zhang, et al., Analysis of users' willingness to continue using mobile medical app from the perspective of information ecology, Data Anal. Knowledge Discovery. 1 (4) (2017) 46–56.
[39] B. Jeffrey, et al., Mobile phone applications and their use in the self-management of Type 2 Diabetes Mellitus: a qualitative study among app users and non-app users, Diabetol. Metab. Syndr. 11 (2019) 84.
[40] L.F. Pitt, R.T. Watson, C.B. Kavan, Service quality: a measure of information systems effectiveness, MIS Q. (1995) 173–187.
[41] S. Petter, W. DeLone, E. McLean, Measuring information systems success: models, dimensions, measures, and interrelationships, Eur. J. Inf. Syst. 17 (3) (2008) 236–263.
[42] S. Baptista, et al., User Experiences With a Type 2 Diabetes Coaching App: Qualitative Study, JMIR diabetes 5 (3) (2020) e16692–e.
[43] X. Guo, et al., Exploring Patients' Intentions for Continuous Usage of mHealth Services: Elaboration-Likelihood Perspective Study, JMIR Mhealth Uhealth 8 (4) (2020) e17258.
[44] K.-L. Hsiao, et al., Continued use intention of lifestyle mobile applications: the Starbucks app in Taiwan, Electron. Libr. 37 (5) (2019) 893–913.
[45] J. Li, et al., Research on the influencing factors of wechat use behavior of elderly users from the perspective of information ecology, Library Inform. Serv. 61 (15) (2017) 25–33.
[46] S. Mellikeche, et al., External validation of the unified model of information systems continuance (UMISC): An international comparison, Int. J. Med. Inf. 134 (2020).
[47] A.D. Beldad, S.M. Hegner, Expanding the Technology Acceptance Model with the Inclusion of Trust, Social Influence, and Health Valuation to Determine the Predictors of German Users' Willingness to Continue using a Fitness App: A Structural Equation Modeling Approach, Int. J. Human-Comput. Interact. (2017).
[48] N.A. Christakis, J.H. Fowler, Social contagion theory: examining dynamic social networks and human behavior, Stat. Med. 32 (4) (2013) 556–577.
[49] R.A. Silver, C. Subramaniam, A. Stylianou, The Impact of Portal Satisfaction on Portal Use and Health-Seeking Behavior: Structural Equation Analysis, J. Med. Internet Res. 22 (3) (2020) e16260.
[50] J. Cohen, Statistical power analysis for the behavioral sciences, Routledge, 2013.
[51] W. Afthanorhan, A comparison of partial least square structural equation modeling (PLS-SEM) and covariance based structural equation modeling (CB-SEM) for confirmatory factor analysis, Int. J. Eng. Innovative Technol. 2 (5) (2013) 198–205.
[52] D.F. Polit, C.T. Beck, The content validity index: are you sure you know what's being reported? Critique and recommendations, Res. Nurs. Health 29 (5) (2006) 489–497.
[53] J.F. Hair Jr, et al., *Advanced issues in partial least squares structural equation modeling*. 2017: saGe publications.
[54] B. Farrugia, WASP (write a scientific paper): An introduction to set-theoretic methods and qualitative comparative analysis, Early Hum. Dev. 133 (2019) 43–47.
[55] C.C. Ragin, J. Sonnett, Between complexity and parsimony: Limited diversity, counterfactual cases, and comparative analysis, in: Vergleichen in der Politikwissenschaft, Springer, 2005, pp. 180–197.
[56] C.C. Ragin, K.A. Drass, S. Davey, Fuzzy-set/qualitative comparative analysis 3.0 23 (2016) 1949–1955.
[57] Y. Liu, et al., Applying configurational analysis to IS behavioural research: a methodological alternative for modelling combinatorial complexities, Inf. Syst. J. 27 (1) (2017) 59–89.
[58] C.C. Ragin, Set relations in social research: Evaluating their consistency and coverage, Polit. Anal. 14 (3) (2006) 291–310.
[59] W.W. Chin, The partial least squares approach to structural equation modeling, Mod. Methods Bus. Res. 295 (2) (1998) 295–336.
[60] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, J. Mark. Res. 18 (1) (1981) 39–50.
[61] C.C. Ragin, Fuzzy-set social science, University of Chicago Press, 2000.
[62] D. Crilly, Predicting stakeholder orientation in the multinational enterprise: A mid-range theory, J. Int. Bus. Stud. 42 (5) (2011) 694–717.
[63] P.C. Fiss, A set-theoretic approach to organizational configurations, Acad. Manag. Rev. 32 (4) (2007) 1180–1198.
[64] P. Duarte, J.C. Pinho, A mixed methods UTAUT2-based approach to assess mobile health adoption, J. Bus. Res. 102 (2019) 140–150.
[65] C.Q. Schneider, C. Wagemann, Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis, Cambridge University Press, 2012.
[66] J.K. Carroll, et al., Who uses mobile phone health apps and does use matter? A secondary data analytics approach, J. Med. Internet Res. 19 (4) (2017) e5604.
[67] N.K. Janz, M.H. Becker, The health belief model: A decade later, Health Educ. Q. 11 (1) (1984) 1–47.
[68] M. Shim, H.S. Jo, What quality factors matter in enhancing the perceived benefits of online health information sites? Application of the updated DeLone and McLean Information Systems Success Model, Int. J. Med. Inf. 137 (2020).
[69] Almazroi, A.A., et al., *An empirical study of factors influencing e-health services adoption among public in Saudi Arabia.* Health Informatics Journal, 2022. **28**(2): p. 14604582221102316.
[70] M. Arnhold, M. Quade, W. Kirch, Mobile applications for diabetics: a systematic review and expert-based usability evaluation considering the special requirements of diabetes patients age 50 years or older, J. Med. Internet Res. 16 (4) (2014) e2968.
[71] L. Nie, et al., Characteristics of Chinese m-Health applications for diabetes self-management, Telemedicine and e-Health 22 (7) (2016) 614–619.
[72] A. Bhattacherjee, A. Barfar, Information Technology Continuance Research: Current State and Future Directions, Asia Pacific J. Inform. Syst. 21 (2) (2011) 1–18.
[73] A. Torres-Quintero, et al., Adaptation of a mobile phone health survey for risk factors for noncommunicable diseases in Colombia: a qualitative study, Glob. Health Action 13 (1) (2020) 1809841.
[74] H. Li, Influencing factors assocated with the continuance intention of health management APP for youth group—Based on the empirical investigation and analysis of Xi'an City, Chongqing University, 2019.
[75] S. Akter, et al., Modelling the impact of mHealth service quality on satisfaction, continuance and quality of life, Behav. Inform. Technol. 32 (12) (2013) 1225–1241.
[76] A. Bhattacherjee, J. Perols, C. Sanford, Information technology continuance: A theoretic extension and empirical test, J. Comput. Inf. Syst. 49 (1) (2008) 17–26.