Understanding health information literacy of mHealth app users from digital wellbeing perspective: Evidence from regression analysis and fsQCA

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Highlights

- Digital wellbeing framework is used to identify what factors improve mHealth apps users' health information literacy (HIL).
- Regression analysis with fuzzy-set qualitative comparative analysis (fsQCA) were combined to validate related factors.
- Person-specific, device-specific, and context-specific factors had independent effects on users' HIL.
- Person-specific, device-specific, and context-specific factors had synergistic effects on users' HIL.

Abstract:

While past research suggests mHealth apps help cultivate users' health information literacy (HIL), factors contributing to their HIL development have not been systematically studied. Applying digital wellbeing framework, an empirical investigation using a large-scale survey dataset was conducted. From regression analysis and fuzzy-set qualitative comparative analysis (fsQCA), two findings were yielded. First, six influential factors, including person-specific factors (i.e., gender, annual family income, internet experience), device-specific factors (i.e., screen sizes of mobile phones), and context-specific factors (i.e., use frequency and perceived quality of mHealth apps), were identified. Second, gender, annual family income, internet experience, screen size of mobile phones, use frequency and perceived quality of mHealth apps had synergistic effects on HIL. By introducing fsQCA to library and information science community, the study not only extends literature by teasing out the combinations of different categories of factors contributing to HIL but informs health professionals and mHealth apps developers.

1. Introduction

Health information literacy (HIL) refers to the extent to which users are able to obtain, use, and understand the information needed to make informed health decisions (Medical Library Association, 2003). Users in the current digital era have relied on mobile devices to stay connected and obtain health information from verified or unverified sources. Against this backdrop, HIL has become increasingly important because it determines one's "abilities to discern good versus bad health information from various information sources […]" (Xie et al., 2020, p. 1421). As a result, users with high HIL can efficiently identify useful and credible health resources to make choices of a healthy lifestyle and self-manage health status (Fu, Chen, & Zheng, 2021). Conversely, users with low HIL might be vulnerable to health-related misinformation and disinformation (Yin & Zhang, 2020). Therefore, it is crucial to improve users' HIL.

In recent years, mobile health applications (hereafter referred to as mHealth apps) are recognized as an emerging healthcare service driven by mobile digital technologies. The apps can facilitate medical knowledge sharing, personal health data recording, and healthcare consultations across the spatiotemporal boundary (Cho, Park, & Lee, 2014; Dehling, Gao, Schneider, & Sunyaev, 2015; Krebs & Duncan, 2015). Given such advantages, mHealth apps have become an important tool for mobile phone users to implement daily health self-management, especially for young adults—typically seen as "digital-savvy"—who depend heavily on mobile phones to keep digitally connected (Fu, Chen, & Deng, 2021). The use of mHealth apps can help them raise HIL through multiple approaches, including healthcare knowledge education, improved autonomous self-regulation and perceived competence (Ghose, Guo, Li, & Dang, in press; Li, Chen, & Bi, 2021). Using mHealth apps on mobile phones may facilitate an active lifestyle and behavior modification. It is not surprising that the global market for mHealth apps is expected to increase at an average rate of 36.5% from 2016 to 2022, reaching a value of 22.31 billion USD by 2022 (Ghose, Guo, Li, & Dang, in press). In China, the domestic market has reached a value of about 3 billion USD in 2020 (CNNIC, 2021).

2. Problem statement

Despite the helpfulness of mHealth apps, users may suffer from many adverse impacts resulting from mobile phone usage, ranging from addiction, anxiety, to technostress (e.g., Dehling, Gao, Schneider, & Sunyaev, 2015; Fu, Chen, & Zheng, 2021; Tarafdar, Cooper, & Stich, 2019). Such phenomena represent the "dark side" of digital technologies, indicating that the relationship between the use of mHealth apps on mobile phones and users' HIL development could be complex. Such a complex relationship implies that mHealth apps users' HIL may be affected by multiple factors. Unfortunately, the current understanding of what factors may help mHealth apps users improve their HIL is limited. To address the gap, this study draws upon a digital wellbeing framework proposed by Abeele (in press). Digital wellbeing refers to the extent to which users may experience (im)balance in relation to mobile connectivity (Abeele, in press). Informed by the digital wellbeing framework, the development of a particular literacy is not only affected by using related apps on mobile phones but also influenced by other factors including users' personality and context of use (Abeele, in press). Hence, the purpose of this study is to identify important factors that may improve mHealth apps users' HIL from the digital wellbeing perspective.

3. Literature review

3.1 Theoretical foundation: Digital wellbeing framework

The theoretical foundation of this study is based on the digital wellbeing framework (Abeele, in press). Digital wellbeing is an important concept in research on mobile technologies and wellbeing (Przybylski & Weinstein, 2017), as it "can inform users, health practitioners, designers, and developers in the industry as well as policymakers about people's struggles with ubiquitous connectivity, and what can be done to help people foster healthier mobile media habits" (Abeele, in press, p. 2). In other words, digital wellbeing can be treated as an umbrella concept that is related to users' cultivation of abilities and literacies by using mobile phones.

The digital wellbeing framework identifies three categories of factors associated with users' particular literacy development. The first category, also known as person-specific factors, refers to users' socio-demographic characteristics such as gender, education level, and income (Mark, Iqbal, Czerwinski, & Johns, 2014). The second, also referred to as device-specific factors, refers to the feature of mobile devices such as screen size (Przybylski & Weinstein, 2017). The third, also grouped as context-specific factors, refers to the boundary conditions of using such mobile devices (Abeele, De Wolf, & Ling, 2018).

Although Abeele's (in press) study suggests that the three categories of factors may eventually influence users' digital wellbeing, her proposed framework lies at a conceptual level, which needs further empirical investigations and validations in a broader context of mobile phones usage. Meanwhile, variables in each category of factors could differ in various usage contexts (Abeele et al., 2018). Nevertheless, there is limited empirical research examining how these factors affect mHealth apps users' HIL.

3.2 Factors related to mHealth apps users' HIL from digital wellbeing framework

Guided by the digital well-being framework, this study anchored on prior research to identify important variables associated with users' HIL and grouped them into three categories of factors, including person-specific, device-specific, and context-specific factors.

In terms of person-specific factors, there are four variables included in the study. First, gender is significantly associated with HIL (Eriksson-Backa, Ek, Niemelä, & Huotari, 2012). For example, among upper secondary school students, the average level of HIL among female students was reported to be higher than that of male students (Niemelä, Ek, Eriksson-Backa, & Huotari, 2012). Second, prior studies on HIL have shown that users with better educational levels tend to have higher HIL (Ivanitskaya, Boyle, & Casey, 2006; Ivanitskaya, Hanisko, Garrison, Janson, & Vibbert, 2012). Third, the family income level of users has been found to have a positive relationship with their HIL (Manganello et al., 2017). Fourth, prior research suggests that users' internet experience might promote their proficiency in identifying reliable health information sources and obtaining needed health information—a manifestation of HIL (Banas, 2008; Fu, Chen, & Deng, 2021).

In terms of device-specific factors, there are two important variables related to mobile phones. First, the proportion of usage time of mHealth apps to the entire mobile phone usage time reflects the strength of users' health awareness (De Nadai, Cardoso, Lima, Lepri, & Oliver, 2019; Li et al., 2020), which is highly associated with HIL. Second, the screen size of mobile phones exerts an impact on users' perceived usability, effectiveness, and efficiency toward mobile phone use (Raptis, Tselios, Kjeldskov, & Skov, 2013), which in turn affects searching and retrieving health information (Sweeney, & Crestani, 2006).

In terms of context-specific factors, there are three significant variables related to mHealth apps use. First, the duration of mHealth apps use may reflect users' engagement with

the apps to improve HIL (Mokhtar, Majid, & Foo, 2006). Second, the use frequency of mHealth apps represents users' habitual health-related information search and use (Webster & Williams, 2005). Third, mHealth apps may also help users identify high-quality health information (Mao, Zhao, & Liu, 2020), as well as make informed health decisions (Donevant, Estrada, Culley, Habing, & Adams, 2018). Therefore, the perceived quality of mHealth apps use is also included in the study.

The digital wellbeing framework argues that different categories of factors may have a synergic effect, indicating that each factor cannot only independently affect users' digital wellbeing but work together to influence digital wellbeing (Abeele, in press). However, such a synergic effect has not been empirically studied.

3.3 Using fsQCA to study synergic effects of different categories of factors of mHealth apps users' HIL

For this study, a fuzzy-set qualitative comparative analysis (fsQCA) is employed to empirically investigate how the person-specific, device-specific, and context-specific factors can work together to affect users' HIL. The use of fsQCA emphasizes the synergistic effects, rather than the independent effects, of a couple of factors (Fiss, 2007). This method is suitable to explore an asymmetric relationship between the factors and their outcomes (Fiss, 2007). The asymmetric relationship indicates that any single factor cannot lead to a given outcome. Rather, the outcome might be caused by a "configuration"— a combination of a group of factors (Park & Mithas, 2020). A factor might influence the outcome only in the absence or presence of another or more additional predictors (Li et al., 2018). Based on the digital welling framework, users' particular literacy might be contingent on several different factors simultaneously (Tseng & Lin, 2008; Enwald et al., 2016; Hirvonen et al., 2016; Mao, Zhao, & Liu, 2020). Hence, fsQCA can uncover multiple configurations among person-specific, device-specific, and context-specific factors that can collaboratively contribute to users' high HIL.

4. Research methodology

4.1. Measures and instrument design

Self-report scales were used to measure the person-specific, device-specific, and context-specific factors of mHealth apps users and their HIL. First, in terms of person-specific factors, this study measured gender, education level, annual family income, and internet experience. Gender included male and female; Education level was assessed as follows: "Year 1," "Year 2," "Year 3," "Year 4," and "Postgraduate." Annual family income was assessed as follows: "no more than 20,000 RMB," "20,000 – no more than 50,000 RMB," "50, 000 – no more than 100, 000 RMB," "100,000 – no more than 200,000 RMB," and "equal or more than 200,000 RMB." Internet experience was assessed as follows: "no more than 0.5 years," "0.5 – no more than 1 year," "1 year – no more than 2 years," "2 years – no more than 3 years," and "equal or more than 3 years."

Second, in terms of device-specific factors, this study asked users to recall the daily time they used their mobile phones, which was assessed as follows: "less than or equal 0.5 hours," "more than 0.5 hour – 1 hour," "more than 1 hour – 3 hours," "more than 3 hours – 5 hours," and "more than 5 hours." Mobile phones' screen size was assessed as follows: "less than 3 inches," "more than 3 inches – 4 inches," "more than 4 inches – 5 inches," "more than 5 inches – 6 inches," and "more than 6 inches."

Third, context-specific factors involve the use duration, use frequency (in a week), and perceived quality of used mHealth apps. Of them, the duration of mHealth app use was assessed

as follows: “less than or equal 0.5 hours,” “more than 0.5 hour – 1 hour,” “more than 1 hour – 2 hours,” and “more than 2 hours.” The use frequency of mHealth app was assessed by the following categories: “less than 1 time every week,” “1 – 2 times every week,” “3 – 5 times every week,” and “6-7 times every week.” Such categorical variables are code into ordinal data in regression analysis. The perceived quality of mHealth apps was measured using a five-item scale developed by Zha, Zhang, Yan, and Xiao (2015). Users were asked to rate on a seven-point Likert scale to indicate the extent to which they agreed with the following five items: “The information in mHealth apps is up-to-date;” “The navigation of mHealth apps is effective;” “The layout of mHealth apps is clear;” “mHealth apps provide personalized services;” and “mHealth apps provide professional services.”

Last, users’ levels of HIL were measured through the use of an adapted version of a widely used scale developed by Niemelä et al. (2012). Specifically, users were asked to assess the extent to which they agreed with the arguments in the following items on a seven-point scale: “I like to get health information from a variety of sources;” “I know where to seek health information;” “It is easy to assess the reliability of health information in printed sources such as magazines and books;” “It is easy to assess the reliability of health information on the internet;” and “I apply health-related information to my own life and/or that of people close to me.” The details are shown in Appendix A.

4.2. Data collection

The target population of this study was young adults who are typically digitally savvy and familiar with mHealth apps. According to the latest report of China Internet Network Information Center, youth have become a significant user group of mHealth apps in China (CNNIC, 2021). Therefore, data were collected in a cross-sectional field survey conducted in a large Chinese University with more than 30,000 undergraduate students. Before the formal data collection, a pilot test was conducted among 10 postgraduate students majoring in information science who had rich experience in using mHealth apps. Based on the feedback from the pilot test, the questionnaire was revised to strengthen the readability and validity of the proposed items.

The final version of the questionnaire was published via the university’s survey platform on the official website of the Physical Education Department (hereafter referred to as the PE department). The PE department of the university conducts sports tests for undergraduates every year. The questionnaire was sent to students randomly when they logged into the official website to view their results of sports tests.

At the beginning of the questionnaire, participants were informed that the survey was only for academic purposes, and the data were collected after obtaining their informed consent. A total of 6,948 responses were initially returned. Of them, incomplete questionnaires and those inappropriate responses were removed; participants failed to correctly answer the questions that this study set to ensure the questionnaire quality (e.g., responding “incorrectly” to reverse-coded items) (Goode, Hoehle, Venkatesh, & Brown, 2017). Removing incomplete and inappropriate questionnaires resulted in 6,160 valid responses. Furthermore, respondents who replied, “I do not know” for the item requesting that they specified the screen size of their mobile phones were excluded (n = 740). Finally, 5,420 valid responses were kept for data analysis.

4.3. Data analysis procedure

4.3.1. Stage 1: Regression analysis

This study adopted a hierarchical ordinary least squares (OLS) regression model to identify influential variables from person-specific, device-specific, and context-specific

factors. In doing so, person-specific factors were entered in Step 1, followed by device-specific factors in Step 2 and context-specific factors in Step 3. In the regression analysis stage, those independent variables that were significantly associated with HIL were determined. Such variables will be included in the stage of fsQCA.

4.3.2. Stage 2: fsQCA

This study then adopted the fuzzy-set qualitative comparative analysis (fsQCA) — which can effectively handle the exponentially increasing complexity of the configurational perspective (Park, El Sawy, & Fiss, 2017), to investigate how these factors worked collaboratively to lead to users' high HIL.

Specifically, in the regression analysis stage, six independent variables were found to be significantly associated with their HIL. They were, namely, gender (GEN), annual family income (AFI), internet experience (ITE), use frequency of mHealth apps (FHA), mHealth app quality (HAQ), and screen size of mobile phones (SSP). Thus, these six variables and the dependent variable, HIL, were selected for the fsQCA analysis.

The qualitative comparative analysis only works for data ranging from 0 to 1. Hence, it is necessary to calibrate the data collected from the field survey before conducting fsQCA. According to the suggestions proposed by previous research (e.g., Li et al., 2018; Liu et al., 2017; Park et al., 2017), this study calibrated the raw data of the selected variables. The calibration process is as follows.

Considering that mHealth app quality and HIL were measured using seven-point Likert scales, four qualitative breakpoints (1, 0.8, 0.2, and 0) were designated to calibrate the two variables following the fsQCA guideline proposed by Liu et al. (2017). Specifically, the original values of 6 and 7 were set to 1 in fsQCA, the original value of 5 to 0.8, the original value of 4 to 0.2, and the rest of the values (3, 2, and 1) to 0. Regarding the dependent variable, HIL, those values ranging from 0.8 to 1 were regarded as "high HIL." Similarly, regarding the independent variable, mHealth app quality, those values ranging from 0.8 to 1 were regarded as "high quality."

For other variables, some were categorical variables such as gender, while some were ordinal variables. This study calibrated these variables based on the following criteria. In terms of categorical variables, this study set them to 0 or 1 according to their influence relationship with HIL in the OLS regression analysis. For example, "male" was calibrated as "0," while "female" was calibrated as "1." Regarding ordinal variables, this study set them to the 0-1 value based on their corresponding rank on the ordinal range. The higher it ranked, the closer to 1 in the calibration.

After data calibration, a truth table was generated by fsQCA, including all logical and plausible combinations of causal conditions. Because this study had six causal conditions, which are GEN (Gender), AFI (Annual Family Income), ITE (Internet Experience), FHA (The Weekly Frequency of Using mHealth Apps), HAQ (The Quality of mHealth Apps), SSP (The Screen Size of Mobile Phones), the ideal combinations of the truth table should be 64 ($64=2^6$). However, the cases in the sample might not necessarily satisfy all possible combinations in the truth table. The truth table must be fine-tuned to isolate relevant configurations by setting frequency cut-off and consistency cut-off (Ragin, 2008). This study considered combinations with at least one case and opted for a consistency threshold above 0.9 because it represents high sufficiency (Park & Mithas, 2020). After that, the truth-table algorithm in fsQCA undertook a counterfactual analysis to handle the combinations without empirical cases and to minimize the number of causal conditions in a configuration (Fiss, 2011). An R package called "QCApro" (Thiem, 2018) was employed to conduct the fsQCA.

The fsQCA uses two measures to validate outcomes. First, consistency measures the extent to which a configuration is sufficient for an outcome to occur (Ragin, 2008). This is roughly comparable to the concept of the significance level in a regression analysis, and a threshold above 0.75 indicates satisfactory consistency (Park & Mithas, 2020). Second, fsQCA uses a coverage measure to validate a configurational outcome. Specifically, raw coverage roughly reflects the degree to which a configuration covers the outcome cases (Ragin, 2008). Unique coverage reflects how uniquely a particular configuration captures cases having the outcome and having no overlap with other configurations (Park et al., 2017). Larger coverage empirically implies more relevant or important configurations (Fiss, 2011). Thus, coverage is a validation measure similar to the coefficient of determination (R^2) in regression analysis and shows the empirical relativity of each configuration to the outcome (Park & Mithas, 2020). If a configuration exceeds the predefined consistency threshold of 0.9, the causal conditions it embodies are sufficient to generate the outcome (Liu et al., 2017; Park et al., 2017).

5. Results

5.1. Sample characteristics

Table 1 shows the demographic breakdown of the sample. Roughly fifty-five percent (55.1%) of the respondents were males, and 44.9% were females. The majority of respondents ranged in education level from Year 1 to Year 4 as undergraduate students (69.89%). The annual family income of most respondents (23.7%) was between 50,000-100,000, whereas only 487 (8.99%) respondents' annual family income was more than 200,000. Finally, 4,276 respondents (78.9%) had more than three years of internet experience.

<Insert Table 1: Demographic statistics for the sample (n = 5,420)>

Table 2 summarizes the mean value, standard deviations of the study variables, and their correlations. In terms of the reliability test, the Cronbach's alpha (α) for HIL and mHealth app quality were 0.93 and 0.97, respectively, indicating an excellent internal consistency for the two scales (Hays & Revicki, 2005). Since some inter-construct correlations were higher than the benchmark of 0.60 (see Table 2), a multicollinearity test was conducted. This study found that all the variance inflation factors (VIFs) were less than 2, eliminating the potential multicollinearity issue (Neter, Kutner, Nachtsheim, & Wasserman, 1996).

<Insert Table 2: Mean, standard deviations, and correlation Matrix (n = 5,420) here>

5.2. Results of regression analysis

As shown in Table 3, person-specific factors including gender ($\beta = 0.066$, $p < 0.05$), annual family income ($\beta = 0.034$, $p < 0.01$) and internet experience ($\beta = 0.051$, $p < 0.01$) were positively related to HIL. One device-specific factor, the screen size of mobile phones ($\beta = 0.130$, $p < 0.001$) showed a significant and positive impact on HIL. Two context-specific factors including the use frequency of mHealth apps ($\beta = 0.057$, $p < 0.01$), and the quality of mHealth apps ($\beta = 0.568$, $p < 0.001$) were positively associated with HIL. However, other factors (i.e., education level, use duration of mobile phone, use duration of mHealth apps) had a non-significant relationship with HIL.

<Insert Table 3: Regression results>

5.3. Results of fsQCA

For the analysis of the necessity of each causal condition, this study found that none of the variables could become a necessary condition of the outcome, high HIL (i.e., values range from 0.8 to 1 in the dataset). Therefore, this study looked for potential configurations of these

causal conditions that lead to high HIL (Park & Mithas, 2020). Table 4 presented the fsQCA results for configurations that produced sufficient conditions for high HIL. In addition, the consistency and coverages (including raw coverage, unique coverages, and solution coverage) are also present in Table 4.

The results showed that four outcomes (i.e., four configurations) produced a high level of HIL. As shown in Table 4, the raw coverage for outcome 1a is 0.343, for outcome 1b is 0.372, for outcome 1c is 0.371, and outcome 2 is 0.154. The overall outcome coverage is 0.445, while the overall outcome consistency is 0.898. Such metrics were satisfactory compared to previous literature (Park et al., 2017). This study makes some key observations as follows.

Among the four configurations, the presence of FHA and HAQ were deemed as necessary conditions because they covered all outcomes. This indicated that in the sample dataset, users who owned high HIL tended to be those who frequently used high-quality mHealth apps regardless of socio-demographic characteristics. Apart from the two conditions, some other conditions were added to lead to the outcome (i.e., high HIL). There are two distinct ways to do this. The first is the use of a small screen size of mobile phones (i.e., the absence of SSP: outcomes 1a, 1b, and 1c). This way especially benefited users who had low annual family income (i.e., the absence of AFI) regardless of their internet experiences were rich or poor.

The second is the use of the big screen size of mobile phones (i.e., the presence of SSP: outcome 2). In this case, male users who had a high level of annual family income (i.e., the presence of AFI) but their internet experiences were poor (i.e., the absence of ITE) were likely to develop high HIL. This study further concludes four combinations for raising high HIL, as shown in Table 5.

<Insert Table 4: fsQCA results for configurations with sufficient conditions>

<Insert Table 5: Combinations for contributing to high HIL in the sample data>

6. Discussion

This study determined important factors that improve the HIL of mHealth apps users from the digital wellbeing perspective. The key findings are two-fold. First, based on the hierarchical OLS regression model, six influential factors of HIL were identified, including person-specific factors (i.e., gender, annual family income, internet experience), device-specific factors (i.e., screen sizes of mobile phones), and context-specific factors (i.e., use frequency of mHealth apps and perceived quality of mHealth apps). Second, using the fsQCA, four main configurations of these influential factors contributing to users' high HIL were proposed, as shown in Table 5.

Consistent with previous research (Niemelä et al., 2012), this study found that, on average, HIL among female users was higher than that among male users. This research has extended the findings of Niemelä et al. (2012) to the college student population. Beyond this, the study further confirmed a positive and conjunctive effect of perceived quality of mHealth apps and use frequency of mHealth apps on users' HIL development regardless of their gender difference.

Configuration 1, configuration 2 and configuration 3 suggested that the perceived quality of mHealth apps and the use frequency were both significant to HIL development among college students. However, configuration 4 showed that in addition to the perceived quality of mHealth apps and the use frequency, male college students with less internet experience had to use a large screen size of mobile phones to improve HIL. In line with the

study of Banas (2008), the results confirmed a positive relationship between users' internet experience and their HIL development, especially for college students. Beyond this, the study further indicated that college students who had inadequate internet experience might benefit from using a large screen size of mobile phones to improve HIL.

Meanwhile, previous studies have drawn inconsistent conclusions regarding mHealth apps' impacts on users' HIL (Manganello et al., 2017; Lin and Bautista, 2017). This study's findings emphasize the importance of mHealth app quality. Only under the premise that the quality of mHealth apps is guaranteed, the use frequency can be positively associated with the users' HIL development.

Last, previous studies on mHealth app use usually view person-specific factors such as gender and internet experience as control variables and analyze their effects in descriptive statistics (Cho et al., 2014; Lin & Bautista, 2017; Manganello et al., 2017), and there is limited knowledge of the configurations among person-specific, device-specific, and context-specific factors. This study suggests that the three categories of factors may collaboratively affect mHealth apps users' HIL.

7. Implications, limitations and future research directions

7.1. Implications for literature

This study contributes to related literature in three ways. First, by drawing upon the digital wellbeing framework, this study advances the understanding of how person-specific, device-specific, and context-specific factors can contribute to users' high HIL. The cultivation of mHealth apps users' HIL is complex and may be affected by multiple factors simultaneously. Past research has not systematically studied how the three categories of factors affect mHealth apps users' HIL, while this study contributes to this research stream using a holistic perspective.

Second, this study extends the literature on health informatics by analyzing the synergistic effects of different factors on users' HIL. As indicated earlier, past research holds the idea that each factor affects their HIL independently. By contrast, this study broadens the viewpoint and argues that it also matters to study how different factors work together to influence users' HIL. For this study, person-specific, device-specific, and context-specific factors are not only associated with users' HIL but also work together to affect HIL. Such findings can complement the existing literature that ignores that different categories of factors may collaboratively affect mHealth apps users' HIL.

Third, this study combines traditional regression analysis with fsQCA to investigate what factors are associated with and how such factors work together to improve mHealth apps users' HIL. As information science researchers are increasingly encouraged to use multi-methods design to address a research question of interest (see Chu & Ke, 2017), this study suggests that information science researchers may consider adopting fsQCA in their own studies and explore some interesting findings that conventional regression analyses cannot derive.

7.2. Implications for practice

The results suggest that HIL development is complex and contingent, which is affected by a variety of factors. Thus, these factors need to be considered when encouraging mHealth app usage among young adults for cultivating HIL. For example, the daily time of using mobile phones may not be positively related to users' HIL but use frequency of mHealth apps matters more. Patients are encouraged to increase their use frequency accordingly. Besides, users with different socio-demographic characteristics such as income and gender may have different

reference points for developing HIL by using mHealth apps. Health professionals should offer customized and personalized suggestions to target users. It may not be wise to encourage all adults to improve their HIL by using mHealth apps.

The results also suggest that it is beneficial to improve the design of their apps to enhance users' quality perceptions and thus motivate them to use the apps regularly. It is also important for developers of mHealth apps to promote users' perceived quality of mHealth apps. For example, it could be feasible for the developers to periodically update the functions of mHealth apps for target user groups. It is also important to design multiple versions of mHealth apps to suit the mobile phone screen size. In this case, post-use surveys can be distributed to understand how they perceive the quality of mHealth apps across different screen sizes.

7.3. Limitations and future research directions

This study has some limitations. First, data were collected from a cross-sectional field survey, which may suffer from the endogeneity issue. In other words, mHealth apps users' HIL could be affected by multiple factors, and in turn, some factors could also be affected by each user's HIL. To address the limitation, future research may employ a longitudinal investigation and conduct a Grange-causality test to see how users' changes of HIL are related to particular person-specific, device-specific, and context-specific factors. Second, the data used in the research were collected in China. Considering that cognitive differences can be found among different national cultures (Ghose et al., 2021), it is unclear whether the findings in this research can be generalized to other countries. To address the limitation, future research may conduct a cross-country comparison. The third limitation is the study's sample, which targeted college students. Although some within this population are digitally savvy and familiar with mHealth apps, the student sample could still pose generalizability questions without further replications and validations. Future research should broaden the target population to replicate the results of this study. It is also meaningful to investigate how older adults or patients with chronic conditions can improve HIL by using mHealth apps.

8. Conclusion

Adopting mHealth apps has been recognized as an effective approach to improving users' health information literacy (HIL). Drawing upon the digital wellbeing framework, this study identified what factors can raise mHealth apps users' HIL. Through an empirical investigation of college students in a public university, this study found that users' gender, annual family income, internet experience, use frequency of mHealth apps, perceived quality of mHealth apps, and screen size of mobile phones had synergistic effects on users' high HIL. Users with high HIL tended to use high-quality mHealth apps frequently. In particular, male users whose internet experiences were limited but annual family incomes were high could own high HIL by frequently using high-quality mHealth apps on a large screen size of mobile phones.

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Appendix A: The measurement of variables

Categories	Variables	Measurements
Dependent variable	Health information literacy	I like to get health information from a variety of sources. I know where to seek health information. It is easy to assess the reliability of health information in printed sources (magazines and books). It is easy to assess the reliability of health information on the Internet. I apply health related information to my own life and/or that of people close to me.
Person-specific factors	Gender	Male Female
	Education level	Year 1 Year 2 Year 3 Year 4 Postgraduate
	Annual family income (RMB)	< 20,000 20,000 – 50,000 (excluding 50,000) 50,000 – 100,000 (excluding 100,000) 100,000-200,000 (excluding 200,000) ≥ 200,000
	Internet experience	< 0.5 year 0.5 year – 1 year (excluding 1 year) 1 year – 2 years (excluding 2 years) 2 years – 3 years (excluding 3 year) ≥ 3 years
Device-specific factors	The daily time of using mobile phones	< 0.5 hour 0.5 hour-1 hour (excluding 1 hour) 1 hour-3 hours (excluding 3 hours) 3 hours-5 hours (excluding 5 hours) ≥ 5 hours
	The screen size of mobile phones	< 3 inches 3 inches-4 inches (excluding 4 inches) 4 inches-5 inches (excluding 5 inches) 5 inches-6 inches (excluding 6 inches) ≥ 6 inches

Context-specific factors	The weekly frequency of using mHealth apps	less than 1 time every week
		1-2 times every week
		3-5 times every week
		6-7 times every week
	The weekly time of using mHealth apps	< 0.5 hour
		0.5 hour-1 hour (excluding 1 hour)
		1 hours-2 hours (excluding 2 hours)
		≥ 2 hours
	The perceived quality of mHealth apps	The information in mHealth apps is up-to-date.
		The navigation of mHealth apps is effective.
		The layout of mHealth apps is clear.
		mHealth apps provide personalized services.
		mHealth apps provide professional services.

Table 1: Demographic statistics for the sample (n = 5,420)

Variable	**Category**	**Count**	**%**
Gender	Male	2,985	55.10
	Female	2,435	44.90
Education level	Year 1	611	11.27
	Year 2	824	15.20
	Year 3	1,039	19.17
	Year 4	1,152	21.25
	Postgraduate	1,794	33.11
Annual family income (RMB)	< 20,000	1,371	25.30
	20,000 – 50,000 (excluding 50,000)	1,284	23.69
	50,000 – 100,000 (excluding 100,000)	1,259	23.23
	100,000-200,000 (excluding 200,000)	1,019	18.80
	≥ 200,000	487	8.99
Internet experience	< 0.5 year	244	4.50
	0.5 year – 1 year (excluding 1 year)	289	5.33
	1 year – 2 years (excluding 2 years)	245	4.52
	2 years – 3 years (excluding 3 year)	366	6.75
	≥ 3 years	4,276	78.89

Table 2: Mean, standard deviations, and correlation matrix (n = 5,420)

Variables	**Mean**	**SD**	**VIF**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1 HIL (dependent variable)	4.192	1.385	1.838	1.000								
2 GEN (person-specific factor)	1.449	0.497	1.033	0.073***								
3 EDU (person-specific factor)	3.497	1.376	1.025	-0.0222	0.038**							
4 AFI (person-specific factor)	2.625	1.287	1.103	0.109***	0.084***	0.049***						
5 ITE (person-specific factor)	4.502	1.096	1.353	0.124***	0.066***	0.096***	0.285***					
6 DTP (device-specific factor)	3.613	1.139	1.271	0.112***	0.128***	0.016	0.090***	0.381***				
7 SSP (device-specific factor)	3.201	0.925	1.231	0.186***	-0.009	-0.053***	0.126***	0.327***	0.335***			
8 FHA (context-specific factor)	1.632	1.017	1.548	0.197***	-0.008	-0.060***	0.047**	0.079***	0.107***	0.108***		
9 THA (context-specific factor)	1.619	0.910	1.519	0.157***	-0.005	-0.012	0.004	-0.042**	0.018	0.042**	0.569***	
10 HAQ (context-specific factor)	3.829	1.556	1.838	0.663***	0.072***	-0.040**	0.081***	0.067***	0.095***	0.124***	0.227***	0.214***

Note: HIL denotes health information literacy; GEN represents gender (1: male; 2: female); EDU represents education level; AFI represents annual family income; ITE represents internet experience; DTP represents the daily time of using mobile phones; SSP represents the screen size of mobile phones; FHA represents the weekly frequency of using mHealth apps; THA represents the weekly time of using mHealth apps; HAQ represents the quality of mHealth apps; SD represents the standard deviation. These abbreviations will also be applied in Table 3 and Table 4. *p< 0.05; **p< 0.01; ***p<0.001.

Table 3: Regression analysis results (n = 5,420)

Independent variables	**Dependent variable: health information literacy (HIL)**					
	Step 1		**Step 2**		**Step 3**	
	β	***t***	***β***	***t***	***β***	***t***
GEN (person-specific factor)	0.171***	4.557	0.175***	4.683	0.066*	2.311
EDU (person-specific factor)	-0.038**	-2.803	-0.024 n.s.	-1.800	0.004 n.s.	0.420
AFI (person-specific factor)	0.083***	5.495	0.077***	5.177	0.034**	3.004
ITE (person-specific factor)	0.129***	7.246	0.051**	2.628	0.051**	3.461
DTP (device-specific factor)			0.038*	2.073	-0.005 n.s.	-0.367
SSP (device-specific factor)			0.228***	10.481	0.130***	7.856
FHA (context-specific factor)					0.057**	3.363
THA (context-specific factor)					-0.008 n.s.	-0.363
HAQ (context-specific factor)					0.568***	60.866
Constant	3.279***	32.410	2.724***	24.469	1.109***	12.298
F test	36.714***		47.226***		503.950***	
R-square	2.6%		5.0%		45.6%	
$\triangle R^2$	2.6%		2.4%		40.6%	

Note: β shows the path coefficient. *t* shows the t-value. R-square shows the proportion of variance in the dependent variable which can be predicted from the independent variables. * $p< 0.05$; ** $p< 0.01$; *** $p< 0.001$; n.s. represents non-significant.

Table 4: Configurations with sufficient conditions based on fsQCA

Configuration		**Causal condition**						**Metrics**				
		GEN	AFI	ITE	FHA	HAQ	SSP	Raw Coverage	Unique Coverage	Consistency	Coverage	Consistency
1	1a		⊗		●	●	⊗	0.343	0.018	0.902	0.445	0.898
	1b			•	●	●	⊗	0.372	0.023	0.893		
	1c				●	●	⊗	0.371	0.021	0.901		
2		⊗	●	⊗	●	●	●	0.154	0.045	0.905		

Note: Black circles indicate the presence of a condition; circles with "X" indicate the absence of a condition. Large circles indicate core conditions; small ones indicate peripheral conditions. Blank spaces indicate "do not care." Overall, solution coverage is the total coverage by all configurations together.

Table 5: Configurations for contributing to high HIL in the sample data

Outcome: High HIL	**Gender**	**Annual family income**	**Internet experience**	**Weekly frequency of mHealth apps use**	**Perceived quality of mHealth apps**	**Screen sizes of mobile phones**
Configuration 1	Male/Female	Low	Rich/Poor	High	High	Small
Configuration 2	Male/Female	High/Low	Rich	High	High	Small
Configuration 3	Male/Female	High/Low	Rich/Poor	High	High	Small
Configuration 4	Male	High	Poor	High	High	Large