Development and validation of a mobile health application usability scale for older adults with chronic diseases

Hongyu Yu, Weiyu Qiu, Yanfeng Wang, Qinyang Wu, Ke Hu, Qiuyun Ye, Qiaohong Yang

Submitted to: JMIR Aging
on: October 22, 2023

Table of Contents

Development and validation of a mobile health application usability scale for older adults with chronic diseases

Hongyu Yu[1*]; Weiyu Qiu[2*]; Yanfeng Wang[1]; Qinyang Wu[1]; Ke Hu[1]; Qiuyun Ye[3]; Qiaohong Yang[1]

[1]School of Nursing, Jinan University Guangzhou CN
[2]The first affiliated hospital of Jinan University Guangzhou CN
[3]Tianhe shipai huashi conmunity health service center Guangzhou CN
[*]these authors contributed equally

Corresponding Author:
Qiaohong Yang
School of Nursing, Jinan University
601 West Huangpu Avenue
Guangzhou
CN

Abstract

Background: Chronic diseases are one of the leading causes of disability and death in people over 60 years. Mobile health applications can revolutionize healthcare delivery and management of chronic conditions as well as reduce healthcare costs. Unfortunately, many of these applications are not designed for elderly patients with chronic diseases. Therefore, it is crucial to create a reliable and specialized tool that developers and researchers can use to assess the usability of mobile (mHealth) applications designed specifically for elderly patients.

Objective: To develop and validate a mHealth application usability evaluation scale for elderly patients with chronic diseases.

Methods: We developed the first edition of the scale from March to September 2022 through literature review, interview, team discussion, and the Delphi method. Between October and December 2022, the improved scale after a pilot test was used to conduct surveys in Guangzhou, Guangdong, China, to analyze and screen items using the Item Discrimination Index, Correlation coefficient, Internal consistency test, and exploratory factor analysis. From October 2022 to February 2023, we completed the data collection and evaluation of the reliability and validity of the scale.

Results: The finalized scale included six dimensions and 23 items. Item-level content validity indices and the average scale content validity index ranged from 0.85–1. The validation evaluation showed that the scale has a good fit, with a ?2/df ratio of 1.728 and various fit indices ranging from 0.817–0.928. The AVE and CR values also met the recommended criteria, with a value greater than 0.4 and 0.6, respectively. Additionally, the Cronbach's ? coefficient for the full scale and subscales ranged from 0.758–0.911, indicating good internal consistency.

Conclusions: The mHealth application usability evaluation scale for older adults with chronic disease was developed with rigorous steps, showing good reliability and validity. The scale can be used to evaluate the usability of mHealth among older adults and promote the age-appropriateness of mHealth.

(JMIR Preprints 22/10/2023:53796)
DOI: https://doi.org/10.2196/preprints.53796

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Development and validation of a mobile health application usability scale for older adults with chronic diseases

Abstract

Background: Chronic diseases are one of the leading causes of disability and death in people over 60 years old. Mobile health applications can revolutionize healthcare delivery and management of chronic conditions and reduce healthcare costs. Unfortunately, many of these applications are not designed for elderly patients with chronic diseases. Therefore, it is crucial to create a reliable and specialized tool that developers and researchers can use to assess the usability of mobile (mHealth) applications designed specifically for elderly patients.

Objective: To develop and validate a mHealth application usability evaluation scale for elderly patients with chronic diseases.

Methods: We developed the first edition of the scale from March to September 2022 through literature review, interview, team discussion, and the Delphi method. Between October and December 2022, the improved scale after a pilot test was used to conduct surveys in Guangzhou, Guangdong, China, to analyze and screen items using the Item Discrimination Index, Correlation coefficient, Internal consistency test, and exploratory factor analysis. From October 2022 to February 2023, we completed the data collection and evaluation of the reliability and validity of the scale.

Results: The finalized scale included six dimensions and 23 items. Item-level content validity indices and the average scale content validity index ranged from 0.85–1. The validation evaluation showed that the scale has a good fit, with a χ^2/df ratio of 1.728 and various fit indices ranging from 0.817–0.928. The values of Average Variance extraction and Composite Reliability also met the recommended criteria, with a value greater than 0.4 and 0.6, respectively. Additionally, the Cronbach's α coefficient for the full scale and subscales ranged from 0.758–0.911, indicating good internal consistency.

Conclusions: The usability scale for elderly patients with chronic diseases is a reliable and valid instrument. It fills gaps in existing tools, offering a comprehensive assessment of mHealth app usability among target audience. It has the potential to improve mHealth app design and promote age-appropriateness of healthcare delivery.

Keywords: MHealth app, usability, instrument development, validation, older adults, chronic diseases

Introduction

As the world's population ages and chronic diseases continue to be prevalent, the care needs of elderly patients are becoming increasingly important. There were over 700 million older people worldwide in 2019, which is set to double by 2050 [1]. Older adults are at increased risk of developing chronic diseases and care dependence; chronic diseases are the leading causes of disability and mortality in people over 60 years [1]. Improving symptom management, sleep quality, health education, self-management ability, and information exchange can help promote health, well-being, and security while reducing social alienation [2]. Failure to meet these needs can result in reduced physical, psychological, and social functions, increased hospitalization, medication complexity, discomfort, decreased quality of life, and even death [3,4]. Additionally, the ongoing course and high complication rate of chronic diseases significantly increase physical and psychological stress on family caregivers and the economic burden on society [5-7]. It is essential to meet the needs of elderly patients with chronic diseases to promote their health and well-being and reduce the burden on caregivers and society.

Mobile health applications (mHealth Apps) have had remarkable effects on the management of chronic diseases, breaking through temporal and spatial barriers of traditional medical service models. These apps support patients through health education, remote monitoring and feedback, and psychosocial interventions, improving medication adherence and lifestyles [8-10]. Patients benefit from improved adherence, promotion of healthy behaviors, enhanced symptom and complication management, better clinical indicators and quality of life, reduced readmissions and mortality, and cost savings on healthcare expenses and trips to the doctor; caregivers also benefit from improved physical and mental health [11-14]. Involving patients with chronic diseases in mHealth is essential.

Without a standardized usability assessment, designing and implementing mHealth apps that meet the needs of elderly individuals with chronic diseases can be challenging. Previously, assessments have relied on interviews and questionnaire surveys. Qualitative data regarding usability can be categorized as positive or negative [18]. Favorable usability encompasses feelings of convenience, usefulness, relaxation, support, and empowerment. In contrast, unfavorable usability is characterized by stress, difficulty, helplessness, mistrust, or a desire to disengage. Questionnaire surveys have gained prominence due to their ease of implementation and data analysis. However, the existing usability assessment tools do not adequately address the unique requirements of mHealth apps tailored for elderly patients with chronic diseases. The System Usability Scale (SUS) [19] and the Post-Study System Usability Questionnaire (PSSUQ) [20] collect user feedback on system usability, but they do not differentiate mHealth apps from other systems. The MHealth App Usability

Questionnaire (MAUQ) [21] was designed to assess mHealth app usability, encompassing aspects like ease of use, efficiency, learnability, and satisfaction. Although the MAUQ has been translated and adapted into various versions [22-24], it still has limitations because individuals over 65 years old or those with limited education were excluded during the development process. Other existing tools also suffer from shortcomings, such as inadequate sampling methods, a lack of a robust theoretical framework, and incomplete evaluations [25, 26]. To address these gaps, we aimed to create and validate a usability scale, named the mHealth app usability scale for the elderly with chronic diseases (MAUS-EC), specifically tailored for mHealth apps intended for older adults with chronic diseases.

Evidence synthesis and theoretical framework

Current evidence suggests various factors that shape their perceptions, experiences, and behaviors toward the acceptance and utilization of mHealth applications among elderly patients with chronic diseases. Firstly, the responsiveness of mHealth apps to individual needs on chronic disease management is crucial for their popularity among users. Positive perceptions regarding the app's ability to facilitate communication with healthcare providers, enhance disease management knowledge, promote a sense of control over health, and foster a proactive approach to monitoring and managing health conditions are key drivers of user engagement. [15, 27-38]. Secondly, while elderly patients appreciate the easy communication options provided by mHealth and find illness management manageable, they also encounter challenges such as difficulty in understanding health education materials, navigating the app, and experiencing technical issues. These usability challenges detract from the overall convenience and effectiveness of mHealth, highlighting the importance of user-friendly design and intuitive interfaces. [15, 17, 27, 33, 34, 38-45]. Thirdly, social influences also play a significant role. Approval and recommendations from family encourage users to embrace these technologies, underscoring the influence of social networks on technology acceptance and utilization. [35, 36, 42]. Fourthly, adequate technical assistance and clear instructions are essential for optimal user experience. Conversely, the absence of technical support and unclear guidelines can impede usability. [35, 36, 42, 43]. Fifthly, reluctance to engage with mHealth stems from factors such as unfamiliarity with electronic devices, challenges in usage, and apprehensions about potential damage or mistakes. Negative past experiences with digital technology and perceived investment of time and effort contribute to resistance toward adoption [17, 29, 34, 33, 40, 45]. Sixthly, privacy and security undermine the trust and confidence of users [31]. Lastly, trust in healthcare professionals and confidence in the effectiveness of mHealth disease management methods are essential for user acceptance. [27, 34-36, 39, 43, 46].

These elements align with the dimensions of the Extended Unified Theory of Acceptance and Use of Technology (Extended UTAUT) model [47, 48], which provides a comprehensive framework for understanding the adoption and utilization of technology. As a result, we have chosen to map the dimensions and scales under the components of this theoretical framework to provide a comprehensive understanding of mHealth adoption among this population.

Methods

Overview

This research project consisted of three parts. In Study 1, literature review, interviews, the Extended Unified Theory of Acceptance and Use of Technology (Extended UTAUT model) [47, 48], and research team discussions were used to form a pool of candidate items. After that, in Study 2, the Delphi method [49] was applied to create the dimensions and items of the initial version of MAUS-EC. We conducted Study 3, which involved a process of item analysis and screening, to identify the most informative items for each domain. Additionally, we evaluated the reliability and validity of the instrument we developed in Study 3.

Ethics

As part of a large-scale research project, this series of studies has been approved by the Medical Ethics Committee of our University (JNUKY-2022-038). Researchers responsible for data collection underwent comprehensive training sessions aimed at addressing stereotypes or biases related to aging, chronic disease, and technology use, as well as enhancing their communication skills. Clear explanations regarding the purpose of the study, the procedures involved, confidentiality measures, and the voluntary nature of participation were provided to all potential participants. Participants were assured that their involvement in the study would not impact their rights to receive healthcare services or lead to any differential treatment. Informed consent was obtained from all participants involved in the development and validation process of the usability scale, ensuring that they understood the study's objectives, procedures, and potential risks and benefits. Furthermore, participants were informed that they had the right to withdraw from the study at any time if they felt uncomfortable or experienced emotional responses or psychological distress due to technological barriers.

Study 1: Assembling a pool of candidate items

Literature Search

Seven English databases and four Chinese databases were searched to collect published research papers on the attitude and experience of elderly patients with chronic diseases using mHealth. The databases included PubMed, Embase, the Cochrane Library, Web of Science, Scopus, CINAHL, ProQuest, The China National Knowledge Infrastructure (CNKI), Weipu (VIP), Wanfang Data, and the Chinese biomedical literature service system (SinoMed). Eligible studies were as follows: (1) Study participants were aged 60 years or older and diagnosed with at least one chronic disease; (2) Research phenomenon: the experience of using mHealth; (3) Research methods: qualitative studies

or mixed-method studies with qualitative results. Methodologies were not limited to descriptive qualitative research, phenomenology, ethnography, and grounded theory. The exclusion criteria were: (1) The full text is unavailable; (2) Mixed-method studies in which qualitative results cannot be extracted; (3) Editorials, conference papers, case reports, and papers without peer review; (4) Non-Chinese and English literature. Relevant MeSH terms and free terms were used to develop search strategies for the databases.

Screening

MHealth as a concept and field of study emerged around the early 2000s [50], so the publication timeline for including literature was limited from January 2000 to March 2022. Figure 1 illustrates the search process using PubMed as an example. Two nursing master's students within our research team independently conducted the screening and initial item development. The study screening and selection process is presented comprehensively using a flow diagram in Figure 2. We formed two initial item pools based on the results from all the included studies. The item pools were then discussed with a nursing professor, and a collective decision was made to form a formal literature-based item pool.

In-depth interviews

We used purposeful sampling to recruit participants from a tertiary hospital in Guangzhou, Guangdong Province, between March and May 2022. To be eligible, participants had to have at least one chronic condition, be 60 years or older, be a current or past user of mHealth, understand and answer the interview questions independently, and provide informed consent. Face-to-face interviews were conducted with patients who provided informed consent. After data collection, the first author supplemented the literature-based items pool.

Research team discussion

A research team consisting of three highly experienced nursing professors specializing in chronic disease management, mHealth, and scale development, two accomplished lecturers with doctorate degrees in Nursing and specialized knowledge in chronic disease care and scale development, one senior clinical nursing expert, and the first author, were assembled to enhance the quality of the items. This team modified items in the pool for Delphi expert review. Furthermore, the team chose potential experts and designed the consultation questionnaire. Following each round of expert consultation, the team discussed the expert opinions and relevant indicators. The team members made appropriate adjustments or deletions and ultimately produced the initial version of the scale.

Study 2: The development of the initial version of MAUS-EC

Recruitment of Experts for the Delphi

The Delphi method was used to ensure anonymous expression of opinions, with multiple rounds of questionnaire surveys and systematic steps to reach basic unanimous views of the experts consulted. To be considered as an expert, candidates had to meet the following criteria: (1) Possess a master's degree or higher; (2) Have at least five years' experience in the healthcare or research of elderly patients with chronic diseases in tertiary hospitals or institutions of higher education or the field of mHealth; (3) Hold the title of deputy senior or higher, although exceptions were made for those with exceptional knowledge and experience; (4) Took part in this research voluntarily and actively collaborated to complete consultations.

The process of identifying qualified experts commenced with the first author conducting a comprehensive search through the publications available on the China National Knowledge Infrastructure (CNKI), which is the largest online literature search database in China. Official website introduction pages of universities and affiliated hospitals were scrutinized to ensure a thorough exploration. Additionally, our team members helped connect experts through their social networks. Pertinent details regarding the potential experts, encompassing their educational background, research focus, and professional designation, alongside their contact information, were meticulously recorded in a Word document. Following this, the research team engaged in extensive discussions aimed at maximizing the diversity of expertise and geographic representation among the identified experts. Subsequently, an electronic version of the consultation questionnaire for the experts was issued through WeChat and NetEase Email Master to invite their involvement in the consultation process and gather their opinions.

Data Collection and Analysis

The Delphi study was initiated online in August 2022. The objectives of our study were communicated to the experts via email, along with the consultation questionnaire. The questionnaire comprised five sections aimed at gathering expert opinions and information. The first section includes a form with 5-point scales for collecting opinions on the importance of dimensions and suggested revisions. The second part included a form with 5-point scales for evaluating the importance value of items, 4-point scales for evaluating the relevance, and suggested modifications. The third section asked experts to rate their familiarity with the information they provided before, using a 5-point scale. The fourth section featured a table for experts to assess the foundation of the basis of their judgment, including practical experience, theoretical knowledge, references, and

personal intuition, graded on a scale of 1–3. Finally, the fifth section was an expert information collection sheet.

The selection process for the Delphi panel experts was conducted meticulously to ensure representation from diverse backgrounds and expertise relevant to the study. Experts were identified through a comprehensive search of reputable sources such as academic databases, professional networks, and industry affiliations. The criteria for expert selection included qualifications such as advanced degrees, extensive experience in healthcare or research related to elderly patients with chronic diseases, and expertise in the field of mobile health (mHealth). After compiling a list of potential experts, invitations were extended to 27 individuals who met these criteria.

During the first round of consultation, experts were provided with detailed information about the study and participation requirements. They were given four weeks to respond to the initial questionnaire, with reminders sent every two weeks to ensure maximum participation. Following a careful review of the responses and incorporation of participants' feedback, adjustments to the scale were made by the first author in consultation with the research team. In the second round of Delphi, the results of the first iteration were shared with all experts who responded to the preliminary survey. This allowed experts to gain insights from their peers and further refine their responses. Similar to the first round, experts were given four weeks to provide feedback. The rationale behind conducting two rounds of Delphi was to facilitate iterative consensus-building among the expert panel, ensuring thorough exploration of diverse perspectives and achieving convergence of opinions. The anonymity of experts was maintained throughout both rounds to encourage candid and unbiased feedback. After the second round of Delphi, the results were collated, and it was found that expert opinions had converged. The consultation process concluded in September 2022. Following minor revisions based on the second round of consultation and discussions within the research team, the initial version of the MAUS-EC was formed.

Study 3. Refining and validating MAUS-EC

Participants and setting

From October 2022 to January 2023, trained investigators used convenience sampling to recruit elderly patients with chronic diseases who had experience using smart devices and mobile applications in a tertiary hospital and two residential communities in Guangzhou, Guangdong. During this phase, participants were selected based on specific inclusion and exclusion criteria. Inclusion criteria encompassed the following: participants had to be elderly individuals aged 60 years or older with a confirmed diagnosis of one or more chronic diseases, such as diabetes, hypertension, heart disease, or respiratory conditions. Exclusion criteria included cognitive impairment or

dementia, severe physical limitations that would impede interaction with smart devices or mobile applications, and lack of prior experience with such technologies.

The participants were required to rate their agreement with items in MAUS-EC on a scale from 1 (strongly disagree) to 5 (strongly agree). Before the formal investigation, 30 elderly patients with chronic diseases pretested the scale to assess its comprehensibility and testability. According to the recommendation [51], a sample size of at least 100 and 200 is required for the Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), respectively. Data analysis was conducted using IBM SPSS Statistics 26.0 and IBM SPSS Amos 28.0.

The apps and tasks required to perform

Before the survey, participants were explained the study objective and the MAUS-EC. They were also provided with a basic introduction and brief demonstration of the mHealth application. Participants were asked to use one of the eight corresponding apps from the Data.ai database with a rating of at least 4.5 and complete specific tasks. The database offers free access to current rankings and market data for apps on iOS and Android App Stores. The apps used were Spring Rain Doctor, Xiaohe Health, Gaoxin Health, Diabetes Nurse, Kidney Online, Dongdong Oncology, Lansheng Brain Doctor, and Respiratory Rehabilitation. The tasks included: (1) registering and logging in to the app; (2) completing personal information, settings, and medical history, and adding physiological indicator records; (3) familiarizing themselves with various modules, browsing, and trying to publish text, pictures, or video information; (4) completing monitoring records and physical and mental condition assessments; (5) contacting healthcare personnel using mHealth to check the instructions and messages received.

Item Analyses

A thorough item analysis and screening procedure were performed using the Item Discrimination Index (IDI), Correlation Analysis, Cronbach's α, and EFA [52]. This approach strategically amalgamates the strengths of different methods while circumventing their respective limitations, ultimately enhancing the robustness and consistency of the screening results [32].

(1) Item Discrimination Index

IDI [53] measures an item's ability to distinguish between high- and low-performing individuals. It is calculated by comparing the proportion of high-scoring individuals who answered an item correctly to the proportion of low-scoring individuals who did the same. The 27^{th} percentile score represents the upper bound of the low-scoring group, and the 73rd percentile score represents the lower bound of the high-scoring group. The critical ratio (CR) is the average difference between high- and low-

scoring groups for each item. An independent sample t-test was then used to compare the scores of these two groups on each item to determine whether the difference was statistically significant; otherwise, the item was considered for removal [53].

(2) Correlation coefficient

The Item-Total Correlation (ITC) is calculated using Pearson Correlation, which measures the correlation between a specific item's score and the overall test score. The Corrected Item-Total Correlation (CITC) accounts for the contribution of the specific item being analyzed to the total score. CITC = ITC * √ (Variance of Total Scores / Variance of Total Scores Excluding the Item). CITC adjusts the correlation to consider the item's variance and its impact on the variance of the total score. Moreover, it provides a more accurate assessment of the item's relationship with the construct being measured. Items with a correlation coefficient above 0.4 are often considered acceptable [53, 54].

(3) Internal consistency test

Cronbach's α [52], a classic index for testing internal consistency test, was used for assessing the internal consistency reliability of the scale. If removing an item increases Cronbach's α, it suggests that the item negatively contributed to the internal consistency of the dimension. This could indicate that the item was not closely related to the other items or that it measured a different aspect of the construct. In this case, removing the item could potentially improve the overall reliability of the dimension.

(4) Exploratory Factor Analysis

EFA [52] is a methodology capable of unveiling latent constructs or dimensions that elucidate the correlations among items. This approach aids in refining the measurement instrument, detecting potential issues with specific items, and acquiring deeper insights into the underlying structure of the phenomenon being measured.

Validity and Reliability assessment

(1) Content validity

Content validity is a fundamental concept that evaluates the extent to which the content of a measurement instrument aligns accurately with the construct it is intended to measure [49]. Two indices are most commonly used to evaluate content validity, including the Item-Level Content Validity Index (I-CVI) and the Average Scale-Level Content Validity Index (S-CVI/Ave) [55]. The I-CVI, derived from the expert consultation questionnaire, is computed by the experts who rated items 3 or 4 for relevance; this count is then divided by the total number of experts consulted. This index measures the proportion of experts who rate a specific item as relevant or appropriate. The S-

CVI/Ave is the average of I-CVI values across all items, reflecting the average agreement among experts regarding the relevance of items within the scale.

(2) Confirmatory Factor Analysis

CFA is a statistical technique employed to evaluate and validate the construct validity of a measurement instrument [52]. Embedded within structural equation modeling (SEM), the primary objective of CFA is to validate whether the hypothesized relationships between the observed items and their latent constructs correspond harmoniously with the theoretical expectations [52]. The Goodness-of-fit Indices used were the Chi-Square divided by Degrees of Freedom (χ^2/df), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), CFI (Comparative Fit Index), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). These Goodness-of-fit Indices help evaluate how well the model aligns with the observed data.

(3) Convergent Validity

Convergent validity [56] measures how well multiple items of the same latent construct or factor in an SEM model are related. It assesses whether different indicators that theoretically are supposed to measure the same construct do so. Standardized factor loadings (SFL) provide insights into how well the indicators measure the underlying constructs. The standard error (SE) reflects the degree of uncertainty in the estimated parameter. Smaller standard errors indicate greater precision in the estimate, while larger standard errors suggest higher uncertainty. Composite reliability (CR) is used to assess the internal consistency or reliability of latent constructs (also known as factors or variables) in an SEM model. The Average Variance Extracted (AVE) was used for measuring the proportion of variance captured by the latent construct about measurement error. Coefficients calculated the correlations between different items measuring the same construct.

(4) Internal Consistency Reliability

We used Cronbach's α to assess how well items in the scale measure the same underlying construct. A higher alpha indicates higher internal consistency.

Results

The pool of candidate items

We developed the pool of candidate items (Table 1) for review by Delphi experts after reviewing 22 original studies, interviewing 19 elderly patients with chronic diseases, and discussing with the research team twice.

Results of two rounds of Delphi expert consultation

Characteristics of the Delphi experts

Twenty experts completed two rounds of consultation. These experts came from 14 universities and six tertiary hospitals located across various regions: Guangdong Province, Anhui Province, Hunan Province, Jiangsu Province, Beijing City, Shanghai City, Zhengzhou City, and Xi'an City. The experts had an average age of 44.55 years (standard deviation [SD] 9.32), with an average relevant research experience of 15 ± 8.5 years. Eleven experts held senior professional titles, and six held deputy senior titles. Furthermore, there were 14 experts with doctoral degrees and six with master's degrees (Table 2).

Experts’ enthusiasm

The response rate of the expert consultation questionnaires reflects the expert positivity coefficient, with a rate over 70% indicating a high positivity [57]. Twenty-seven inquiry questionnaires were sent in the first round, yielding 20 responses completed with expert opinions and insights, resulting in a commendable positive coefficient of 74.1%. In the second round, 20 consultation questionnaires were issued, and the suggestions and opinions of experts were also obtained. The expert positivity coefficient reached 100%. Both rounds achieved positive coefficients meeting the recommended criteria, demonstrating the active engagement, and significant investment of experts in this research project.

Expert Authority Coefficient

The Expert Authority Coefficient is used to determine the experts’ level of authority or influence in the context of this study. Cognitive Authority (Ca) was calculated based on experts’ self-evaluation judgment. Cr was calculated from (Ca +Cs) / 2. As shown in Table 3, the authority coefficient of both rounds was higher than 0.7, indicating that the degree of authority was good and the consultation results were reliable [53].

Coordination Degree of Experts

The average importance and the full score ratio reflect the concentration of experts' opinions on the article. In the first and second rounds of correspondence, the average importance of each item ranged from 3.37–5 and 4.1–4.9, and the full score ratio ranged from 0.22–1 and 0.45–0.9, respectively.

Expert Opinion Coordination Degree Index

The degree of coordination of experts' opinions is measured by the Coefficient of Variation (CV). In the first and second rounds of consultation, the CV of each item ranged from 0 to 0.5 and 0.063 to 0.37, respectively. The results of these two rounds of inquiry were statistically significant ($P<0.05$).

Initial Version of MAUS-EC

Experts provided their input on dimensions and items. Dimensions and items were deleted or modified based on the experts' feedback, considering three key indicators and our team discussions. As shown in Table 4, items with a Mean Importance Score (MIS) of ≤ 3.50, a Full-Scale Ratio (FSR) of ≤ 0.2, or a CV of ≥ 0.25 were subject to modification or removal [53]. Following the initial round of inquiries, 13 items were removed, and 13 were modified. There were suggestions for adding three items. Items 19 and 20 were merged into a single item, as were items 21 and 22, along with items 36 and 37. Based on the feedback and evaluation criteria of the experts and following our group discussions, six items were removed, and four were modified. Items 23 and 26 were merged into a single item, as were items 34 and 35 (Table 4). After two rounds of expert consultation, the initial version of MAUS-EC was constructed to comprise six dimensions and 32 items. These dimensions encompassed nine items for Perceived Usefulness, nine for Perceived Ease of Use, four for Facilitating Conditions, three for Technology Anxiety, three for Perceived Safety, and four for Professional Trust.

Refinement and Validation of MAUS-E

Polit survey results indicate that the scale items are clearly constructed and easily understandable. However, we have observed that all the items within the same dimension were either all positive or all negative, with no alternating positive and negative items. This presents a potential risk of response bias. Therefore, we made adjustments to the following items: (1) "MHealth allows me to get health information and support from fellow patients" was modified to "MHealth has not enabled me to obtain health information and support from fellow patients (-)"; (2) "I am more confident in managing my illness" was modified to "I still lack confidence in managing my illness (-)"; (3) "Managing my illness with mHealth is not difficult for me" was modified to "Managing my illness with mHealth is difficult for me (-)"; (4) "MHealth frequently lags, making it difficult to use (-)" was modified to "MHealth is smooth, I find it user-friendly"; (5) "I am not familiar with electronic devices, and using mHealth makes me nervous (-)" was modified to "I am familiar with electronic devices, using mHealth does not make me nervous"; (6) "MHealth may leak my personal and health information, so I think it is unsafe (-)" was modified to "MHealth will not disclose my personal and

health information, I feel secure."

Results of Item Analysis and Screening

We collected 175 valid responses during this stage: 109 (62.3%) from males and 66 (37.7%) from females. Among these respondents, 93 (53.1%) in the were between 60–69 years age group, 62 (35.4%) in the 70–79 age group, and the remaining 20 individuals (11.4%) were aged between 80 and 92. One hundred (57.1%) participants resided in urban areas, and 133 (76%) were married. The educational background of the participants was as follows: primary school or below, 78/175 (44.6%); junior high school, 69/175 (39.4%); high school or vocational education, 22/175 (12.6%); and college or above, 6/175 (0.3%). Among all respondents, 32.6% had an average monthly household income of less than 2000 yuan, 60.6% had an income between 2001 and 6000 yuan, and 0.7% had an income exceeding 6000 yuan.

(1) Item Discrimination Index

As depicted in Table 5, the results of the independent sample t-test have revealed that only items 20 and 30 did not display a significant difference ($p > 0.05$). In such a scenario, if the items exhibit a critical ratio (CR value) < 3 [53], it signifies poor discrimination and may be considered for removal. Additionally, all items, except for items 20 and 30, demonstrated effective discrimination.

(2) Correlation coefficient

Table 5 reveals that several items do not meet the thresholds and can be considered for deletion. Specifically, Items 1, 2, 9, 17–22, 26, 28, 29, 31, and 32 did not satisfy the criteria of ITC ≥ 0.4; they also did not demonstrate a significant difference ($p < 0.05$) or have a CITC ≥ 0.4.

(3) Internal consistency test

Cronbach's α values were computed for each dimension, with the following results: Dimension 1 (Items 1–9), Dimension 2 (Items 10–18), Dimension 3 (Items 19–22), Dimension 4 (Items 23–25), Dimension 5 (Items 26–28), and Dimension 6 (Items 29–32) had a value of 0.712, 0.774, 0.524, 0.817, 0.758, and 0.686, respectively. After removing Items 9, 18, 26, and 29, the Cronbach's α values for the corresponding dimension improved by 0.094, 0.022, 0.034, and 0.072, respectively. Considering other relevant indicators, it was advisable to reconsider the exclusion of Dimension 3. But Cronbach's α coefficient of dimension 3 cannot meet the minimum requirement of 0.6 [58], and its items 19~22 should be considered for deletion.

(4) Exploratory factor analysis

After analysis, the Kaiser-Meyer-Olkin (KMO) value was found to be 0.789, and Bartlett’s sphericity test was statistically significant ($P < 0.05$), indicating that it was appropriate to conduct EFA [59, 60]. Six factors were extracted based on the criterion of eigenvalues greater than 1. The scree plot in

Figure 3 illustrates a transition from steep to stable, indicating a satisfactory factor solution. The cumulative variance contribution rate reached 68.12%, exceeding the 60% threshold, which suggests that the model is acceptable [52]. We eliminated two cross-loaded items, Items 7 and 8, although their factor loadings were more than 0.4.

In summary, items 7–9, 18–22, and 29 were removed (Table 5). We, therefore, obtained a scale of 23 items in six dimensions and began the validation survey and analysis.

Reliability and validity evaluation of MAUS-EC

Two hundred respondents (males: 124/200, 62%; females: 76/200, 36%) completed this validation survey; 107 were aged between 60 and 69 years old (53.5%), 68 participants were aged between 70 and 79, and 25 individuals were aged 80 or above (12.5%). In total, 155 (77.5%) people resided in urban areas, while 45 (22.5%) lived in rural areas, respectively. The majority of participants were married (185/200). More than half of the respondents (116/200) had at least a junior high school education (junior high school: 63/200, 31.5%; high school or vocational school: 42/200, 21%; college or higher: 11/200, 5.5%). The average monthly family income was stratified as follows: 2000 yuan or less (94/200, 47%), 2001 to 6000 yuan (94/200, 47%), and more than 6000 yuan (12/200, 6%). One yuan is approximately equal to 0.14 US dollars.

Evaluation of scale reliability and validity

(1) Content validity

The I-CVI ranged from 0.85–1, which aligns with the minimum requirement of 0.78 [55]. Furthermore, the average S-CVI was 0.97, exceeding the specified threshold of 0.9 [55].

(2) Structural validity

The model formed by CFA (Figure 4) grouped four items: Item 14—"The font and icons are too small to see (-)"; Item 15—"Sharper contrast in text and background colors is needed (-)"; Item 16—"Adding disease measurement results manually on mHealth is annoying (-)"; and Item 17—"MHealth brings inconvenience due to lack of synchronization of diagnosis and treatment information in different hospitals (-), into a single dimension". Parameter estimates for this model all met the criteria (Table 6), indicating that this new model better aligns with the observed data compared to the initial model. The formed dimension was, therefore, renamed "Access Empowerment".

(3) Convergent Validity

The SFL, AVE, and CR were greater than 0.5, 0.4, and 0.6, respectively (Table 7). These results align with the established standards [65-68].

(4) Reliability evaluation

As shown in Table 8, the Cronbach's α of MAUS-EC was 0.85, and the Cronbach's α coefficients for dimensions 1–6 were 0.813, 0.911, 0.854, 0.858, 0.788, and 0.758, respectively. All Cronbach's α coefficients exceeded 0.7 and were in the acceptable range [69].

Discussion

This study reports on the development of a scale (MAUS-EC) to measure the usability of mHealth apps among older adults with chronic diseases and also assessed its psychometric proprieties among a sample of older Chinese adults. This scale has 23 items in six domains to operationalize the usability, providing researchers and stakeholders with a reliable and valid instrument to improve the age-appropriateness of mHealth.

Compared with previous usability testing tools, such as SUS, PSSUQ, and MAUQ [19-21], we adopted a series of organized and standardized empirical studies focused on elderly patients with chronic diseases. The development of scale items is based on a systematic literature review and the existing framework, showing a solid theoretical foundation. In-depth interviews extended information relating to the interactions between the patients and mHealth. Our experienced research team members promoted the accuracy and readability of the items through discussion. The Delphi method was used to further modify the scale items, conducted among experts from the central, northern, and eastern regions as well as the southern coastal areas of China. Their expertise included chronic disease care, aging care, and mHealth. These observations reflect the geographical and professional representation of the experts. The Delphi survey also gave them sufficient time and energy to consult relevant materials, enrich background knowledge, think more thoroughly, and express their views fully about the scale through "back-to-back" communication [49]. A pilot survey using a small sample strengthened the feasibility of measurement.

In this study, we analyzed the differentiation, representativeness, independence, and internal consistency of all items. We found that the items performed well in terms of differentiation, which may be related to systematic development progress and multiple revisions. The initial version of MAUS-EC formulated after two rounds of expert consultation, consisted of 32 items, each meeting the selection criteria for stability [52]. We referred to relevant indicators and combined expertise during the item screening process. CFA was conducted to examine the factor structure, resulting in six dimensions (perceived usefulness, perceived ease of use, access empowerment, technology

anxiety, perceived security, and professional trust) forming the final version of MAUS-EC. These dimensions encompass various aspects of the use of mHealth for elderly patients with chronic diseases, including cognitive, behavioral, physiological, and psychological factors. The comprehensiveness of the scale dimensions ensures that what is measured under each dimension is different. Employing a one-size-fits-all tool, such as the System Usability Scale (SUS) [19], for assessing usability is problematic. This is especially evident when considering the unique challenges faced by aging individuals living with chronic conditions since they have their own set of needs and experiences when interacting with mHealth apps. While there may be some overlap with dimensions such as ease of use, ease of learning, simplicity, effectiveness, information, and user interface in PSSUQ [20], these characteristics alone do not capture the diverse complexities involved. The MAUQ [21] faces even more significant challenges, as it excludes older adults without a high school or higher education and those aged outside the range of 18 to 65 years in its development. However, our tool effectively addresses these gaps, ensuring inclusivity and relevance.

The first subdimension (items 1 to 6), which is perceived usefulness, refers to the extent to which an older patient believes that using mHealth would enhance their chronic disease management. A system characterized by high perceived usefulness is one where users perceive a positive relationship between its use and their performance outcomes [70]. Higher scores in this dimension indicate that users perceive the application as providing valuable support in their healthcare management, thereby enhancing overall usability. Perceived ease of use, the second subdimension across items 7 to 10, refers to the degree to which an individual believes that using the mHealth application would require minimal effort. Effort is a finite resource that individuals allocate to chronic disease management. Consequently, all else being equal, an application perceived to be easier to use than another is more likely to be accepted by users [70]. Higher scores in this dimension indicate that users find the application easy to use and navigate, leading to improved usability. Access empowerment is the third subdimension (items 11 to 14). pertains to the technical support mHealth provides for the population. It evaluates the extent to which users feel empowered to access and utilize the application to manage their health independently. Higher scores in this dimension indicate that users feel confident and empowered in utilizing the application.

The fourth subdimension (items 15 to 17), technology anxiety [71], addresses the negative emotions that may arise when using mHealth. This dimension addresses the negative emotions that may arise when using mHealth applications, such as anxiety or discomfort related to technology use. Lower scores in this dimension indicate lower levels of technology anxiety, leading to improved usability. Perceived Security - the fifth subdimension (items 18, 19, and 20), concerns the degree to

which users believe their personal information can be secured when using mHealth applications. It evaluates users' perceptions of data confidentiality, integrity, and protection from unauthorized access or misuse, which is similar to the subjective judgment on perceived security risk among healthcare practitioners [72]. Higher scores in this dimension indicate greater trust and confidence in the security measures of the application, thereby enhancing usability by fostering user trust and engagement.

Items 20 to 23 are professional trust that measures the degree of trust in the professionalism of mHealth applications. It assesses users' perceptions of the accuracy, relevance, and credibility of health information provided through the application. Higher scores in this dimension indicate greater trust in the credibility and reliability of the application, enhancing usability by promoting user satisfaction and adherence to health recommendations.

In summary, MAUS-EC was developed through a theory-driven and evidence-based approach while following the principles of the development process, reflecting good reliability and validity. The qualitative and quantitative evaluation and the screening of the items met the requirements of psychometrics. This feasible scale helps evaluate the usability of mHealth apps from the perspective of older adults with chronic diseases. The instrument is also easy to understand, without redundant items, and it has a suitable number of items for older adults with chronic diseases to respond to. Future research should focus more on improving the usability of mHealth and enhancing the age-appropriateness of the healthcare delivery model in the evolving digital environment through this tool. Particular attention should be paid to individuals with low scores to reduce digital health inequalities.

Implications

The development of the mHealth application usability scale for older adults with chronic diseases has profound implications beyond design and implementation. It catalyzes ongoing research and innovation in mobile health, fostering collaboration across the healthcare ecosystem to improve the relevance, trustworthiness, security, and accessibility of mobile health solutions. By translating research findings into actionable strategies, stakeholders can collectively enhance the quality of care and life for elderly patients with chronic conditions.

Participatory design, involving end users throughout the iterative design process [73], will form the foundation for prototype features and functions tailored to address the management needs and priorities of older adults. Multidisciplinary teams, including clinician-scientists, user experience researchers, app designers, and developers, collaborate systematically to develop applications that

adhere to established principles. Leveraging collective expertise, these teams address usability barriers identified through the scale, enhancing user engagement and adherence to digital self-care solutions. Simplified interfaces, enhanced navigation aids, and consistent wearable devices aim to reduce physical and cognitive load for older adults. Education on privacy and data security features addresses concerns about personal information, fostering trust in the application. Additionally, gamification elements and reward systems make applications more engaging and less anxious, incentivizing users to achieve their health goals. The effective translation of new knowledge, social technologies, and engagement techniques holds the promise of yielding novel approaches for empowering, engaging, and educating older adults with chronic diseases [74].

Continuous evaluation and refinement of mHealth apps, facilitated through usability scales, ensure their feasibility and effectiveness in meeting the evolving needs of older adults with chronic diseases. Insights gleaned from usability assessments play a crucial role in shaping healthcare policy and guiding the development of guidelines and standards for mobile health application design. Policymakers are thus empowered to advocate for user-centered design principles and robust testing protocols, thereby enhancing the quality and safety of mobile health interventions and fostering trust among users and healthcare providers. Moreover, perceived value, acting as a mediator in mobile app usage intention and promotion strategies [75], can be further bolstered through appropriate propaganda. In this context, APP operators may employ fear-based advertising strategies to incentivize users to adopt security protection measures and related software services [76], thereby reinforcing the overall efficacy and acceptance of mobile health applications.

A comprehensive onboarding process is vital in ensuring that older adults can effectively utilize mHealth apps. This process not only guides users through the initial setup and use of the application but also provides personalized training resources and accessible help channels, which are essential for overcoming any technological challenges they may face. However, the role of social workers, support communities, and caregivers cannot be overstated in this context [77]. They play a crucial role in empowering older adults to embrace and navigate these digital health solutions with confidence. Through their assistance, guidance, and education efforts, they not only enhance access empowerment but also alleviate the technology anxiety that users may experience. This fosters a supportive and inclusive environment where older adults feel encouraged to embrace digital health solutions, leading to improved engagement and ultimately better health outcomes.

Further research directions could include testing the scale's applicability in longitudinal studies to assess its sensitivity to changes over time among older adults with chronic diseases. Moreover, exploring the scale's effectiveness in different cultural contexts would offer valuable insights into its

cross-cultural validity and usability. These future research endeavors would contribute to refining the scale's utility and ensuring its effectiveness across diverse populations and settings, ultimately enhancing its impact on the design and implementation of mobile health solutions for elderly patients with chronic conditions.

Limitations

The limitations of this study should be acknowledged for a comprehensive understanding of its findings. Firstly, the elderly patients with chronic diseases surveyed were exclusively from Guangzhou City, Guangdong Province in China, representing an urban setting. To ensure the scale's applicability to rural older adults, future research should include participants from rural areas. Moreover, China's culture of collectivism and family-centeredness may influence older adults' perceptions of mobile health applications, potentially impacting usability. Cultural factors should be considered when interpreting the study's results and adapting the usability scale for use in diverse cultural contexts. Additionally, the study's cross-sectional design limits its ability to assess the long-term usability of mHealth applications. Longitudinal studies would be beneficial to evaluate the sustained usability and effectiveness of these applications among older adults with chronic diseases. Furthermore, the mHealth apps examined in this study represent only a subset of those available on the market. Including a wider range of samples and considering additional usability factors process would enhance its utility for designing and developing mHealth apps tailored to the intended user base.

Conclusions

Our study introduces the Mobile Health Application Usability Scale for Elderly Patients with Chronic Diseases (MAUS-EC), a robust instrument developed through systematic empirical studies and expert consultation. With 23 items across six domains, MAUS-EC demonstrates good reliability and validity, offering researchers and stakeholders a comprehensive tool to assess the usability of mHealth apps among older adults with chronic diseases. Its multidimensional structure addresses various aspects of usability, filling gaps left by previous tools and ensuring inclusivity, relevance, and applicability across diverse user demographics. MAUS-EC's subdimensions capture key factors such as perceived usefulness, ease of use, access empowerment, technology anxiety, perceived security, and professional trust, providing a nuanced understanding of mHealth app usability. Future

research should leverage MAUS-EC to drive improvements in mHealth app design and enhance healthcare delivery models for aging populations in digital environments.

Abbreviations

CFA: Confirmatory Factor Analysis

CITC: Corrected Item-Total Correlation

CNKI: China National Knowledge Infrastructure

CV: Coefficient of Variation

EFA: Exploratory Factor Analysis

FSR: Full-Scale Ratio

GFI: Goodness-of-Fit Index

IDI: Item Discrimination Index

ITC: Item-Total Correlation

KMO: Kaiser-Meyer-Olkin

MAUQ: MHealth App Usability Questionnaire

MIS: Mean Importance Score

SEM: Structural equation modeling

Acknowledgments

We want to extend our sincerest appreciation to both the patients and experts who selflessly took part in this research. Their significant contributions and unique perspectives have greatly enhanced our comprehension and advanced our knowledge of this field.

Conflicts of Interest

None.

References

[1] United Nations. Department of economic and social affairs. Population division. World population ageing, 2019: highlights. https://digitallibrary.un.org/record/3846855 (Accessed: October 14, 2021).

[2] Wang Y, Tang L, Yue L, Zhao Y, Han X. Research progress on the demands of supportive home care for elderly patients with chronic diseases. Chin Nurs Res 2021;35(16):2946. doi:CNKI:SUN:SXHZ.0.2021-16-026.

[3] Palmer K, Villani ER, Vetrano DL, et al. Association of polypharmacy and hyperpolypharmacy with frailty states: a systematic review and meta-analysis. Eur Geriatr Med. 2019;10(1):9-36. PMID: 32720270. doi:10.1007/s41999-018-0124-5

[4] Clegg A, Young J, Iliffe S, Rikkert MO, Rockwood K. Frailty in elderly people [published correction appears in Lancet. 2013 Oct 19;382(9901):1328]. Lancet. 2013;381(9868):752-762. PMID: 23395245. doi:10.1016/S0140-6736(12)62167-9

[5] Duran Parra M, Torres CC, Arboleda LB, Rivera Carvajal R, Franco S, Santos J. Effectiveness of an Educational Nursing Intervention on Caring Ability and Burden in Family Caregivers of Patients with Chronic Non-Communicable Diseases. A Preventive Randomized Controlled Clinical Trial. Invest Educ Enferm. 2019;37(1):e04. PMID: 31083841. doi:10.17533/udea.iee.v37n1e04

[6] Murphy A, Palafox B, Walli-Attaei M, et al. The household economic burden of non-communicable diseases in 18 countries. BMJ Glob Health. 2020;5(2):e002040. Published 2020 Feb 11. PMID: 32133191. doi:10.1136/bmjgh-2019-002040

[7] Allegrante JP, Wells MT, Peterson JC. Interventions to Support Behavioral Self-Management of Chronic Diseases. Annu Rev Public Health. 2019;40:127-146. PMID: 30601717. doi:10.1146/annurev-publhealth-040218-044008

[8] Hanlon P, Daines L, Campbell C, McKinstry B, Weller D, Pinnock H. Telehealth Interventions to Support Self-Management of Long-Term Conditions: A Systematic Metareview of Diabetes, Heart Failure, Asthma, Chronic Obstructive Pulmonary Disease, and Cancer. J Med Internet Res. 2017;19(5):e172. PMID: 28526671. doi:10.2196/jmir.6688

[9] Hamine S, Gerth-Guyette E, Faulx D, Green BB, Ginsburg AS. Impact of mHealth chronic disease management on treatment adherence and patient outcomes: a systematic review. J Med Internet Res. 2015;17(2):e52. PMID: 25803266. doi:10.2196/jmir.3951

[10] Kitsiou S, Paré G, Jaana M. Effects of home telemonitoring interventions on patients with chronic heart failure: an overview of systematic reviews. J Med Internet Res. 2015;17(3):e63. Published 2015 Mar 12. PMID: 25768664. doi:10.2196/jmir.4174

[11]Chi NC, Demiris G. A systematic review of telehealth tools and interventions to support family caregivers. J Telemed Telecare. 2015;21(1):37-44. PMID: 25475220. doi:10.1177/1357633X14562734

[12] Fitzner KK, Heckinger E, Tulas KM, Specker J, McKoy J. Telehealth technologies: changing the way we deliver efficacious and cost-effective diabetes self-management education. J Health Care Poor Underserved. 2014;25(4):1853-1897. PMID: 25418248. doi:10.1353/hpu.2014.0157

[13] Yang X, Kovarik CL. A systematic review of mobile health interventions in China: Identifying gaps in care. J Telemed Telecare. 2021;27(1):3-22. PMID: 31319759. doi:10.1177/1357633X19856746.

[14] Li Y, Li J, Zhang Y, Ding Y, Hu X. The effectiveness of e-health interventions on caregiver burden, depression, and quality of life in informal caregivers of patients with cancer: A systematic review and meta-analysis of randomized controlled trials. Int J Nurs Stud 2022;127:104179. PMID: 35124473.

[15] Sanders C, Rogers A, Bowen R, et al. Exploring barriers to participation and adoption of telehealth and telecare within the Whole System Demonstrator trial: a qualitative study. BMC Health Serv Res. 2012;12:220. PMID: 22834978. doi:10.1186/1472-6963-12-220

[16] Williams V, Price J, Hardinge M, Tarassenko L, Farmer A. Using a mobile health application to support self-management in COPD: a qualitative study. Br J Gen Pract. 2014;64(624):e392-e400. PMID: 24982491. doi:10.3399/bjgp14X680473

[17] Cajita MI, Hodgson NA, Lam KW, Yoo S, Han HR. Facilitators of and Barriers to mHealth Adoption in Older Adults With Heart Failure. Comput Inform Nurs. 2018;36(8):376-382. PMID: 29742549. doi:10.1097/CIN.0000000000000442

[18] Xiong J, Yu H, Su J, Zhao Z, Yang Q. Meta-synthesis of qualitative research on the experience of elderly patients with chronic disease participating in telemedicine. Chin J Nurs. 2022;57(13):1641-1649. doi:CNKI:SUN:ZHHL.0.2022-13-014.

[19] Brooke J. SUS: A "quick and dirty" usability scale. In: Jordan PW, Thomas BA, Weerdmeester B, McClelland IL, editors. Usability evaluation in industry. London: Taylor & Francis; 1996. p. 189-194. url={https://api.semanticscholar.org/CorpusID:107686571

[20] Lewis JR. Psychometric evaluation of the post-study system usability questionnaire: The PSSUQ. Human Factors Society 36th Annual Meeting; Atlanta: Human Factors and Ergonomics Society; 1992. p. 1259-1263. doi: https://doi.org/10.1177/154193129203601617

[21] Zhou L, Bao J, Setiawan IMA, Saptono A, Parmanto B. The mHealth App Usability Questionnaire (MAUQ): Development and Validation Study. JMIR Mhealth Uhealth. 2019;7(4):e11500. PMID: 30973342. doi:10.2196/11500

[22] Shan Y, Ji M, Xie W, et al. Chinese Version of the Mobile Health App Usability Questionnaire: Translation, Adaptation, and Validation Study. JMIR Form Res. 2022;6(7):e37933. PMID: 35793132. doi:10.2196/37933

[23] Quifer-Rada P, Aguilar-Camprubí L, Gómez-Sebastià I, Padró-Arocas A, Mena-Tudela D. Spanish version of the mHealth app usability questionnaire (MAUQ) and adaptation to breastfeeding support apps. Int J Med Inform. 2023;174:105062. PMID: 37037124. doi:10.1016/j.ijmedinf.2023.105062.

[24] Mustafa N, Safii NS, Jaffar A, et al. Malay Version of the mHealth App Usability Questionnaire (M-MAUQ): Translation, Adaptation, and Validation Study. JMIR Mhealth Uhealth. 2021;9(2):e24457. PMID: 33538704. doi:10.2196/24457

[25] Nimmanterdwong Z, Boonviriya S, Tangkijvanich P. Human-Centered Design of Mobile Health Apps for Older Adults: Systematic Review and Narrative Synthesis. JMIR Mhealth Uhealth. 2022 Jan 14;10(1):e29512. PMID: 35029535. doi:10.2196/29512

[26] Matthew-Maich N, Harris L, Ploeg J, Markle-Reid M, Valaitis R, Ibrahim S, Gafni A, Isaacs S. Designing, Implementing, and Evaluating Mobile Health Technologies for Managing Chronic Conditions in Older Adults: A Scoping Review. JMIR Mhealth Uhealth. 2016 Jun 9;4(2):e29. PMID: 27282195. doi:10.2196/mhealth.5127

[27] Fairbrother P, Pinnock H, Hanley J, McCloughan L, Sheikh A, Pagliari C, McKinstry B; TELESCOT programme team. Continuity, but at what cost? The impact of telemonitoring COPD on continuities of care: a qualitative study. Prim Care Respir J. 2012 Sep;21(3):322-8. PMID: 22875143. doi:10.4104/pcrj.2012.00068

[28] O'Cathain A, Drabble SJ, Foster A, Horspool K, Edwards L, Thomas C, Salisbury C. Being Human: A Qualitative Interview Study Exploring Why a Telehealth Intervention for Management of Chronic Conditions Had a Modest Effect. J Med Internet Res. 2016 Jun 30;18(6):e163. PMID: 27363434. doi:10.2196/jmir.5879

[29] Bond CS, Worswick L. Self Management and Telehealth: Lessons Learnt from the Evaluation of a Dorset Telehealth Program. Patient. 2015 Aug;8(4):311-6. PMID: 25315192.

[30] Korpershoek YJG, Vervoort SCJM, Trappenburg JCA, Schuurmans MJ. Perceptions of patients with chronic obstructive pulmonary disease and their health care providers towards using mHealth for self-management of exacerbations: a qualitative study. BMC Health Serv Res. 2018 Oct 4;18(1):757. PMID: 30286761.

[31] Selman L, McDermott K, Donesky D, Citron T, Howie-Esquivel J. Appropriateness and acceptability of a Tele-Yoga intervention for people with heart failure and chronic obstructive

pulmonary disease: qualitative findings from a controlled pilot study. BMC Complement Altern Med. 2015 Feb 7;15:21. PMID: 25887324. doi:10.1186/s12906-015-0540-8

[32] Fairbrother P, Pinnock H, Hanley J, McCloughan L, Sheikh A, Pagliari C, McKinstry B. Exploring telemonitoring and self-management by patients with chronic obstructive pulmonary disease: a qualitative study embedded in a randomized controlled trial. Patient Educ Couns. 2013 Dec;93(3):403-10. PMID: 23647981. doi:10.1016/j.pec.2013.04.003

[33] Lyngå P, Fridlund B, Langius-Eklöf A, Bohm K. Perceptions of transmission of body weight and telemonitoring in patients with heart failure? Int J Qual Stud Health Well-being. 2013 Dec 16;8:21524. PMID: 24345687. doi:10.3402/qhw.v8i0.21524

[34] Chang CP, Lee TT, Mills ME. Experience of Home Telehealth Technology in Older Patients With Diabetes. Comput Inform Nurs. 2017 Oct;35(10):530-537. PMID: 28291156. doi:10.1097/CIN.0000000000000341

[35] Huniche L, Dinesen B, Nielsen C, Grann O, Toft E. Patients' use of self-monitored readings for managing everyday life with COPD: a qualitative study. Telemed J E Health. 2013 May;19(5):396-402. PMID: 23531094. doi:10.1089/tmj.2012.0135

[36] Hägglund E, Strömberg A, Hagerman I, Lyngå P. Theory Testing of Patient Perspectives Using a Mobile Health Technology System in Heart Failure Self-care. J Cardiovasc Nurs. 2019 Nov/Dec;34(6):448-453. PMID: 31365443. doi:10.1097/JCN.0000000000000595

[37] Fairbrother P, Ure J, Hanley J, McCloughan L, Denvir M, Sheikh A, McKinstry B; Telescot programme team. Telemonitoring for chronic heart failure: the views of patients and healthcare professionals - a qualitative study. J Clin Nurs. 2014 Jan;23(1-2):132-44. PMID: 23451899. doi:10.1111/jocn.12137

[38] Ladin K, Porteny T, Perugini JM, Gonzales KM, Aufort KE, Levine SK, Wong JB, Isakova T, Rifkin D, Gordon EJ, Rossi A, Koch-Weser S, Weiner DE. Perceptions of Telehealth vs In-Person Visits Among Older Adults With Advanced Kidney Disease, Care Partners, and Clinicians. JAMA Netw Open. 2021 Dec 1;4(12):e2137193. PMID: 34870680. doi:10.1001/jamanetworkopen.2021.37193

[39] Hanley J, Fairbrother P, McCloughan L, Pagliari C, Paterson M, Pinnock H, Sheikh A, Wild S, McKinstry B. Qualitative study of telemonitoring of blood glucose and blood pressure in type 2 diabetes. BMJ Open. 2015 Dec 23;5(12):e008896. PMID: 26700275. doi:10.1136/bmjopen-2015-008896

[40] Lundell S, Modig M, Holmner Å, Wadell K. Perceptions of Home Telemonitoring Use Among Patients With Chronic Obstructive Pulmonary Disease: Qualitative Study. JMIR Mhealth Uhealth. 2020 Jun 3;8(6):e16343. PMID: 32490844. doi:10.2196/16343

[41] Chunhan L. Xiaocen Q, Mao S, Xi X, Jinlian L. The experiences of low acceptance of mHealth apps in patients with heart failure: a qualitative study. Chinese Journal of New Clinical Medicine. 2021,14(12):1238-1241. doi:CNKI:SUN:ZYLN.0.2021-12-018.

[42] Poppe L, Crombez G, De Bourdeaudhuij I, Van der Mispel C, Shadid S, Verloigne M. Experiences and Opinions of Adults with Type 2 Diabetes Regarding a Self-Regulation-Based eHealth Intervention Targeting Physical Activity and Sedentary Behaviour. Int J Environ Res Public Health. 2018 May 10;15(5):954. PMID: 29748460. doi:10.3390/ijerph15050954

[43] Vergouw JW, Smits-Pelser H, Kars MC, van Houwelingen T, van Os-Medendorp H, Kort H, Bleijenberg N. Needs, barriers and facilitators of older adults towards eHealth in general practice: a qualitative study. Prim Health Care Res Dev. 2020 Dec 2;21:e54. PMID: 33263272. doi:10.1017/S1463423620000547

[44] Sultan M, Kuluski K, McIsaac WJ, Cafazzo JA, Seto E. Turning challenges into design principles: Telemonitoring systems for patients with multiple chronic conditions. Health Informatics J. 2019 Dec;25(4):1188-1200. PMID: 29320911. doi:10.1177/1460458217749882

[45] Portz JD, Bayliss EA, Bull S, Boxer RS, Bekelman DB, Gleason K, Czaja S. Using the Technology Acceptance Model to Explore User Experience, Intent to Use, and Use Behavior of a Patient Portal Among Older Adults With Multiple Chronic Conditions: Descriptive Qualitative Study. J Med Internet Res. 2019 Apr 8;21(4):e11604. PMID: 30958272. doi:10.2196/11604

[46] Korpershoek YJG, Vervoort SCJM, Trappenburg JCA, Schuurmans MJ. Perceptions of patients with chronic obstructive pulmonary disease and their health care providers towards using mHealth for self-management of exacerbations: a qualitative study. BMC Health Serv Res. 2018 Oct 4;18(1):757. PMID: 30286761. doi:10.1186/s12913-018-3545-4

[47] Hoque R, Sorwar G. Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. Int J Med Inform. 2017 May;101:75-84. PMID: 28347450. doi:10.1016/j.ijmedinf.2017.02.002

[48] Cimperman M, Makovec Brenčič M, Trkman P. Analyzing older users' home telehealth services acceptance behavior-applying an Extended UTAUT model. Int J Med Inform. 2016 Jun; 90:22-31. PMID: 27103194. doi:10.1016/j.ijmedinf.2016.03.002

[49] Turoff M, Linstone HA. The Delphi method-techniques and applications. URL: https://api.semanticscholar.org/CorpusID:65474994

[50] Istepanian RSH, Laxminaryan S. UNWIRED: the next generation of wireless and internetable telemedicine systems-editorial paper. IEEE Trans Inform Technol Biomed. 2000;4:189-194. PMID: 11026588. doi: 10.1109/TITB.2000.5956074

[51] Ni P, Chen J, Liu N. Sample size estimation for quantitative research in nursing studies. Chinese Journal of Nursing. 2010;45(4):378-380. doi:CNKI:SUN:ZHHL.0.2010-04-044.

[52] Wang Y. Development and Evaluation of Medical Scales: Theory, Methods, and Practical Examples. Peking University Medical Press. 2010.

[53] Wu M. Practical Statistical Analysis for Questionnaires. Chongqing University Press. 2010.

[54] Zhou J. Questionnaire Data Analysis: Unveiling Six Analytical Approaches for SPSS. Electronic Industry Press. 2017.

[55] Shi J, Mo X, Sun Z. Application of Content Validity Index in Scale Development. Journal of Central South University (Medical Edition). 2012;37(2):49-52. doi:CNKI:SUN:HNYD.0.2012-02-009.

[56] Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate Data Analysis (8th ed.). Cengage Learning. 2019.

[57] Qu J, Zhu, Qu B. Application of the Delphi method in medical education research. Chinese Journal of Medical Education. 2019;39(03):227-230.

[58] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis. Pearson College Division.

[59] Sun S. Medical Multivariate Statistics and Statistical Software. Beijing: Peking University Medical Press, 2000.

[60] Zhang W. SPSS 11 Statistical Analysis Tutorial - Advanced Edition: World-Class Statistical Tools. Beijing: Beijing Hope Electronic Press, 2002.

[61] Xiang J, Ning Li, Chen Y, et al. Development and Reliability and Validity Testing of the Self-Management Behavior Assessment Scale for Lung Cancer Survivors. Chinese Journal of Nursing. 2022;57(21):2615-2621. doi:CNKI:SUN:ZHHL.0.2022-21-008.

[62] Marsh HW, Balla JR, McDonald RP. Goodness-of-fit indexes in confirmatory factor analysis: The effect of sample size. Psychological bulletin. 1988;103(3):391. URL: https://api.semanticscholar.org/CorpusID:144185621

[63] Hair JF. Multivariate data analysis. 2009.

[64] Kline RB. Principles and practice of structural equation modeling. Guilford publications. 2015.

[65] Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research. 1981;18(1):39-50. doi: https://doi.org/10.1177/002224378101800104

[66] Lam LW. Impact of competitiveness on salespeople's commitment and performance. Journal of Business Research. 2012;65(9):1328-1334. doi: https://doi.org/10.1016/j.jbusres.2011.10.026.

[67] Fornell C, Larcker DF. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research. 1981;18(1):39-50. doi: https://doi.org/10.1177/002224378101800104

[68] Chen W, Huang C, Mao T, Luo J, Zhang J. SEM Analysis of the Convergence and Discriminant Validity of Multidimensional Assessment Tools—Using the Perceived Social Support Scale as an Example. Journal of Southwest University (Natural Science Edition). 2016;41(02):136-140.

[69] George D, Mallery P. SPSS for Windows step by step: A simple guide and reference. 11.0 update (4th ed.). Boston: Allyn & Bacon; 2003.

[70] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319−340. doi: https://doi.org/10.2307/249008

[71] Guo, X., Sun, Y., Wang, N., Peng, Z., & Yan, Z. (2013). The dark side of elderly acceptance of preventive mobile health services in China. Electronic Markets, 23, 49-61. URL: https://api.semanticscholar.org/CorpusID:16578139

[72] Alexandrou, A., & Chen, L. C. (2019). A security risk perception model for the adoption of mobile devices in the healthcare industry. Security Journal, 32, 410-434. URL: https://api.semanticscholar.org/CorpusID:18560783

[73] McCurdie, T., Taneva, S., Casselman, M., Yeung, M., McDaniel, C., Ho, W., & Cafazzo, J. (2012). mHealth consumer apps: the case for user-centered design. Biomedical instrumentation & technology, Suppl, 49–56. doi: https://doi.org/10.2345/0899-8205-46.s2.49

[74] Stellefson, M., Chaney, B., Barry, A. E., Chavarria, E., Tennant, B., Walsh-Childers, K., Sriram, P. S., & Zagora, J. (2013). Web 2.0 chronic disease self-management for older adults: a systematic review. Journal of medical Internet research, 15(2), e35. doi: https://doi.org/10.2196/jmir.2439

[75] Zhu, P., Wang, Z., Li, X., Liu, Y. H., & Zhu, X. (2020). Understanding promotion framing effect on purchase intention of elderly mobile app consumers. Electronic Commerce Research and Applications, 44(November-December), Article 101010. doi: https://doi.org/10.1016/j.elerap.2020.101010

[76] Zhu, P., Hu, J., & Zhu, X. (2020). Research on the Influence of Fear Appeal on APP Users'

Privacy Protection Behavior: An Empirical Study. IOP Conference Series: Materials Science and Engineering, 782. doi: 10.1088/1757-899X/782/4/042011

[77] Kleinman, A., Chen, H., Levkoff, S. E., Forsyth, A., Bloom, D. E., Yip, W., Khanna, T., Walsh, C. J., Perry, D., Seely, E. W., Kleinman, A. S., Zhang, Y., Wang, Y., Jing, J., Pan, T., An, N., Bai, Z., Wang, J., Liu, Q., & Habbal, F. (2021). Social Technology: An Interdisciplinary Approach to Improving Care for Older Adults. Frontiers in public health, 9, 729149. doi: https://doi.org/10.3389/fpubh.2021.729149

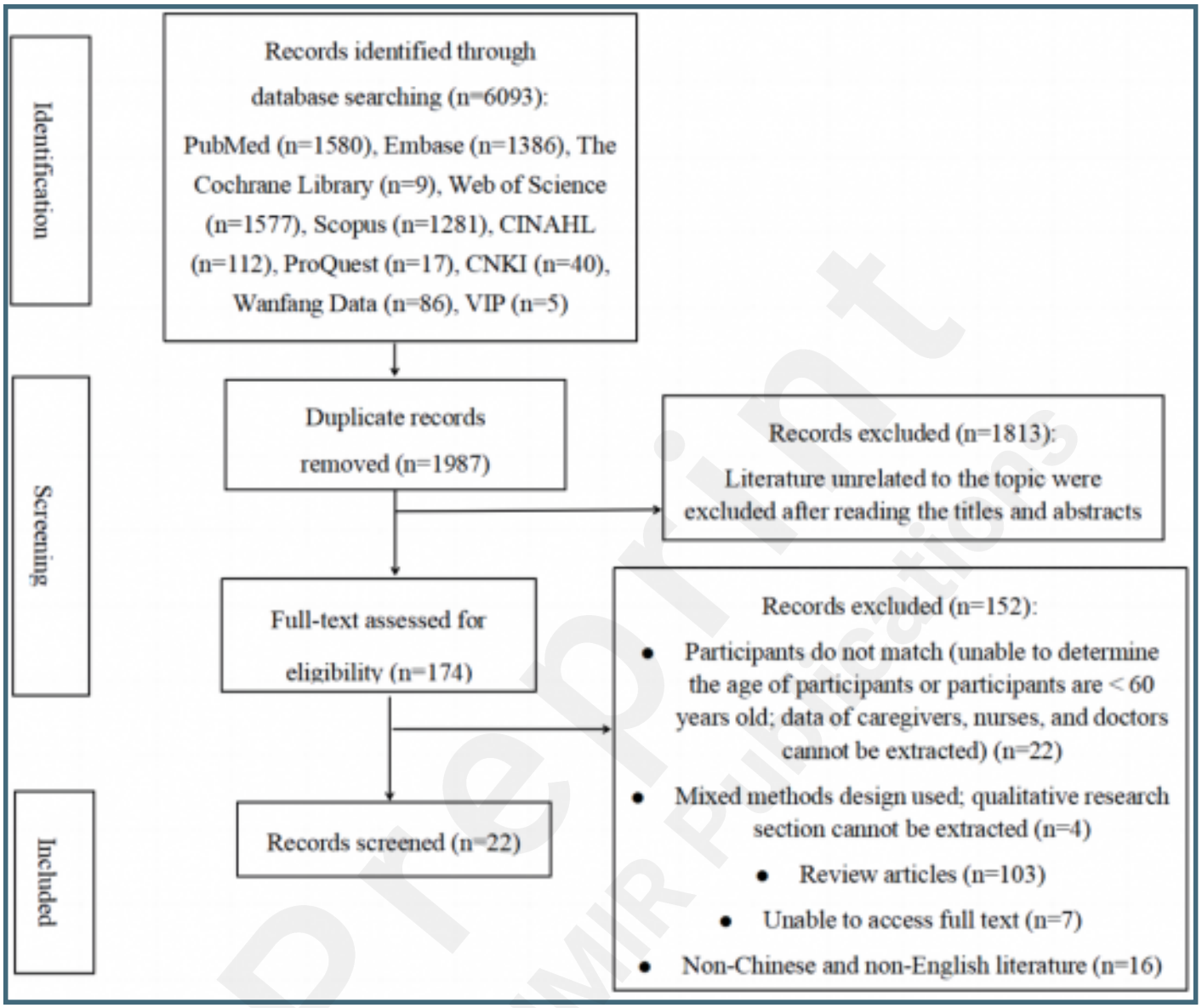
Supplementary Files

Figures

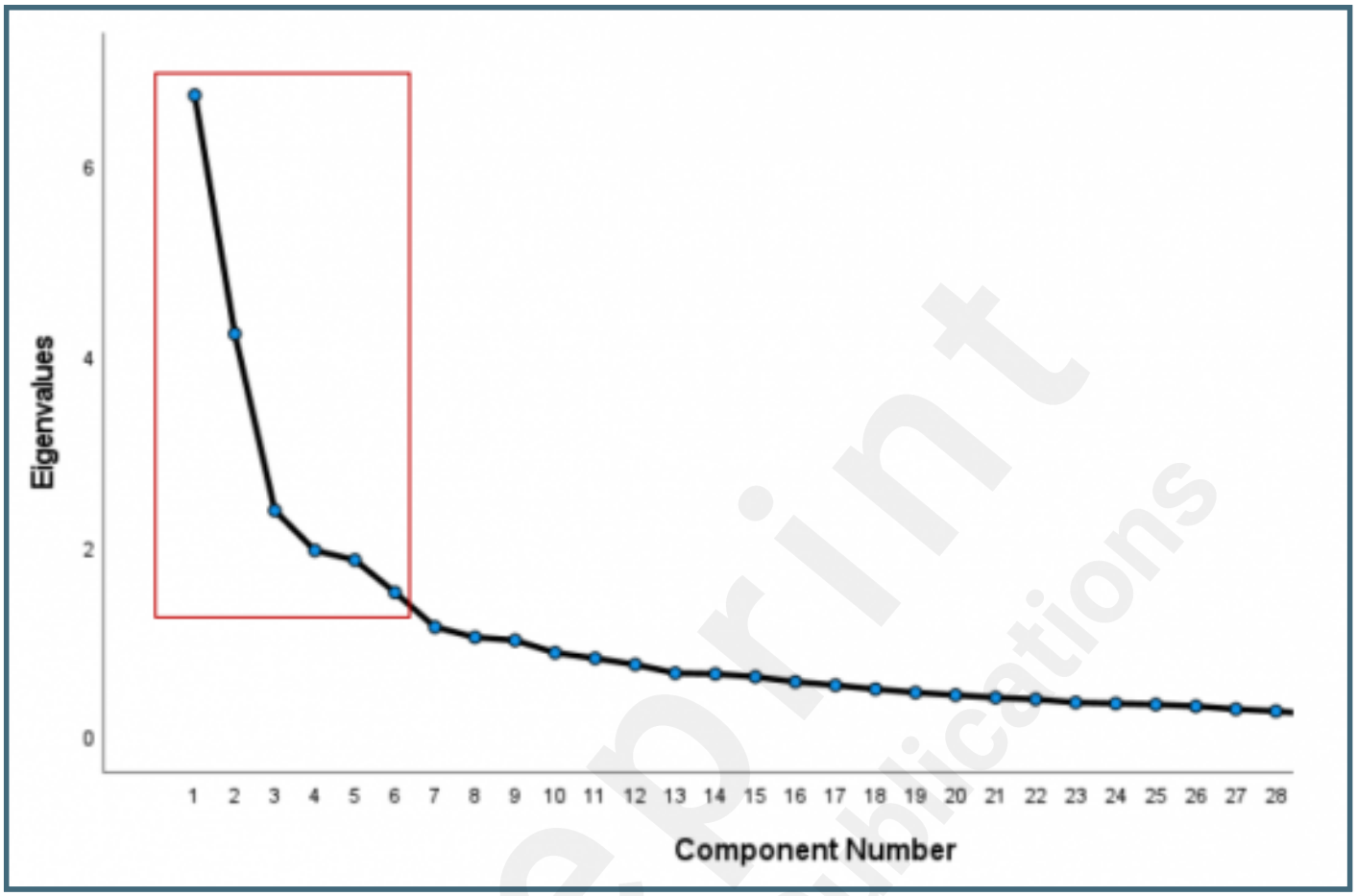
The search strategy used in PubMed.

("Older adults" OR "Elderly" OR "Senior citizens" OR "Aging population" OR "Older individuals") AND ("Hypertension" OR "Diabetes" OR "Heart disease" OR "Arthritis" OR "Chronic obstructive pulmonary disease" OR "COPD" OR "Osteoporosis") AND ("mHealth" OR "Mobile health" OR "Mobile applications" OR "Smartphone apps" OR "Mobile technology") AND ("Attitude" OR "Perception" OR "Opinion" OR "Viewpoint" OR "Sentiment") AND ("Experience" OR "User experience" OR "Patient experience" OR "Lived experience") AND ("Ethnography" OR "Phenomenology" OR "Grounded theory" OR "Narrative analysis" OR "Content analysis" OR "Thematic analysis")

The study screening and selection process.



Gravel diagram.



Multimedia Appendixes

Table 1. The pool of candidate items.
URL: http://asset.jmir.pub/assets/280d78f3bffc1a3ff78ca76ca63c9a49.docx

Table 2. Delphi experts' demographics.
URL: http://asset.jmir.pub/assets/fc78fc6b53ceb33a92b8dd011c44142a.docx

Table 3. The Expert Positivity Coefficient.
URL: http://asset.jmir.pub/assets/b4c989460e75a00ef979d266ae74bfd0.docx

Table 4. Indicators of two rounds of Delphi consultation and the screening results.
URL: http://asset.jmir.pub/assets/cdb8acaeafe5bb8943bc55d5f3684f37.docx

Table 5. Item analysis and screening.
URL: http://asset.jmir.pub/assets/5eaa48eeed2349349b24b97443213763.docx

Table 6. Fit indices of the structural equation models.
URL: http://asset.jmir.pub/assets/3a2bacee16c321e15bd99d7f36ee47ea.docx

Table 7. Indicators of convergent validity.
URL: http://asset.jmir.pub/assets/88229eddb6d2ab63979e8d74f78ffe30.docx

Table 8. Cronbach's ? of MAUS-EC and the subscales.
URL: http://asset.jmir.pub/assets/0ebdcafee17ca3586a969c61f63848e8.docx