Understanding Acceptance of Healthcare Technology Among Older Adults Through TAM and UTAUT: Systematic Review and Meta-Analysis

Hyo Jun Yang, Ji-Hyun Lee, Wonjae Lee

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Abstract

Background: To understand the acceptance of healthcare technology for older adults, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) is commonly used. However, the divergence in the current literature makes it difficult to predict acceptance and understand how various factors affect older adults' behavior.

Objective: This study aims to 1) determine the influence of perceived usefulness (PU), perceived ease of use (PEOU), and social influence (SI) on the behavioral intention (BI) to use healthcare technology among older adults and 2) and assess the moderating effects of age, gender, geographic region, type of healthcare technology, and the presence of visual demonstrations on these three pairwise relationships.

Methods: Google Scholar, Web of Science, Scopus, IEEE Xplore, and ProQuest electronic databases were searched from inception to February 2024. Two independent reviewers screened the titles, abstracts, full texts, and performed data extraction and risk of bias assessments with the Newcastle-Ottawa Quality Assessment Scale. The "meta" package in R was used for data synthesis, conducting random-effects meta-analyses, meta-regression and subgroup analysis.

Results: 41 studies with a total of 11,574 participants were included. Random-effects meta-analyses showed significant positive correlations for PU-BI ($r = 0.607$, 95% CI 0.543 - 0.665, $P < .001$), PEOU-BI ($r = 0.525$, 95% CI 0.462 - 0.583, $P < .001$), and SI-BI ($r = 0.551$, 95% CI 0.468 - 0.624, $P < .001$). Moderator analyses indicated significant differences in effect sizes based on geographic region for PEOU-BI (Q-test, $P = .04$), type of technology for PU-BI (Q-test, $P = .04$) and SI-BI (Q-test, $P = .002$), and presence of visual demonstrations for PU-BI (Q-test, $P = .03$) and SI-BI (Q-test, $P = .04$).

Conclusions: The findings indicate that PU, PEOU, SI significantly impact the acceptance of healthcare technology among older adults, with heterogeneity influenced by geographic region, type of technology, and presence of visual demonstrations. Researchers should account for these variables when interpreting previous research and embarking on new studies with the TAM or UTAUT model for older adults. Clinical Trial: Current paper is not RCT

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Trial Registration: Current paper is not RCT

Keywords: Technology adoption; older adults; healthcare technology; technology acceptance model; unified theory of acceptance and use of technology; meta-analysis

Introduction

Background

According to the United Nations, the number of people aged 65 and older is projected to be 1.6 billion in 2050, which is double of what it was in 2021 [1], and the number of persons aged 80 years and older is projected to be 143 million in 2050, triple what it was in 2019 [2]. This demographic shift raises significant concerns for the escalating burden on healthcare systems and associated financial implications. With advanced age often comes a higher prevalence of chronic illnesses and age-related conditions, necessitating increased medical attention and resources [3, 4].

Technology can play a role in supporting older adults in healthcare by allowing quicker information and communication, preventing the development of chronic conditions, and monitoring health conditions [5]. At the same time, they can also reduce caregiver burden, leading to cheaper and better quality care [6]. However, despite the potential benefits offered by these advancements, their widespread adoption remains limited, primarily due to ambivalence among older adults towards technology acceptance [7]. Therefore, identifying the factors that affect the acceptance of technology for older adults is one of the most important research needs to support older adults' use of technology [8].

However, a key issue is that the current literature that aims to understand the acceptance of healthcare technology for older adults exhibits significant heterogeneity, with diverse studies yielding varying effects and strengths of predictors [9]. To explain, the Technology Acceptance Model (TAM) [10] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [11] are commonly used by scholars to understand technology in the context of health [12] and were applied in research of different types of healthcare technology and their acceptance by older adults [13, 14, 15]. TAM uses perceived usefulness (PU) and perceived ease of use (PEOU), with the subsequent TAM2 adding subjective norm (SN), while UTAUT identifies performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions as core determinants to explain behavior intention (BI). The constructs of TAM and UTAUT can be combined due to their conceptual similarities and complementary nature and previous studies have utilized the findings of both models in meta-analysis [16]. PU and PE both reflect the belief that using technology will enhance performance, while PEOU and EE indicate the perceived effort required to use the technology. SI, akin to SN in TAM2, addresses the influence of important others on technology usage. Both models use the constructs to explain behavior intention (BI), the intention to adopt technology.

To elaborate the heterogeneity of the TAM and UTAUT literature, studies have shown that older adults are more likely to accept technology that meets their needs and expectations [17, 18]. However, the impact of PU on technology acceptance varies for healthcare technology. Li et al. found that PU had very little impact on the behavior intention to adopt a remote health management service for older adults [19] while Mahmood & Lee reported a high influence of PU for health monitoring wearable technology [20]. For older adults, ease of use is crucial because physical and cognitive abilities affect the acceptance and use of technology [21, 22]. However, studies are conflicting. Wu et al. identified a high effect for the acceptance of medical self-service terminals [23], but Khan et al. observed a low effect for mobile health services [24]. Similarly for SI, while it is understood SI can significantly affect older adults' technology adoption, particularly those from their children, friends, and professional caregivers [25], heterogeneity exists in the current literature. Koo et al. detected a high effect of SI for the acceptance of a personalized health care service app [26] while Wong et al. determined that SI had no effect on the use of the Internet for health information in one of the two models used in the study [27].

Such heterogeneity makes it difficult to interpret results because the inconsistent findings across studies prevent a clear, unified understanding of the effects of PU, PEOU, and SI on BI for healthcare technology acceptance among older adults. This study aims to perform a meta-analysis to systematically aggregate and analyze these diverse results, providing a more robust and comprehensive assessment of the factors influencing healthcare technology adoption in this population and the characteristics of the primary studies that have moderating effects. Similar research, such as the quantitative meta-analysis by Chong et al. provided an expansive study into the TAM and UTAUT literature on healthcare information technologies but did not focus on older adults and was limited to a specific type of healthcare technology [16], while Ma et al. focused on literature that applied the two models for older adults for without specifying the type of technology [28]. Therefore, a meta-analysis that specifically targeted older adults and their acceptance of different types of healthcare technology is needed to provide a more defined analysis of the current literature.

Objectives

To ensure a clearer interpretation of the current literature regarding the acceptance of healthcare technology for older adults, this study aimed to:

1. Synthesize the sample size weighted average of the PU-BI, PEOU-BI, and SI-BI relationships for current the current literature that utilized TAM or UTAUT to examine the acceptance of healthcare technology for older adults
2. Identify sources of systematic heterogeneity by analyzing the sample and methodology characteristics of the primary studies that moderate the PU-BI, PEOU-BI, and SI-BI relationships.

Methods

Literature Search

To ensure a comprehensive aggregation of studies exploring the acceptance of healthcare technology by older and aging adults through TAM and UTAUT frameworks, an extensive multi-database search was conducted. The databases used were Google Scholar, Web of Science, Scopus, IEEE Xplore, and ProQuest. A combination of three groups of word strings were developed for the search using logical operators (AND/OR): (1) Age-related keywords were "older adults" or "elderly" or "ageing" or "aging". (2) Theoretical framework keywords were "unified theory of acceptance and use of technology" or "UTAUT" or "technology acceptance model" or "TAM" or "acceptance" or "adoption" or "intention". (3) Context of use keywords were "health" or "healthcare" or "well-being" or "gerontechnology". The number of articles identified, screened, eligible and included were recorded according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement.

Eligibility Criteria

Two researchers independently screened all the titles and abstracts to identify studies eligible for full-text screening. Any disagreements were resolved through a majority vote after involving a third researcher. To ensure the selected studies were directly relevant to the research question, the following inclusion criteria were established for full-text screening:

1. The study utilized the TAM, including the perceived usefulness, and perceived ease of use construct, or the UTAUT, including performance expectancy and effort expectancy. Social norm or social influence construct was not required as they are not as commonly used.
2. The study reported the zero-order correlation between PU-BI, and PEOU-BI.
3. The study involved a technology that aims to improve health or give access to health information.

If a study's sample included two or more of the same characteristics (participants from both Asia and Europe, survey regarding multiple types of technology, etc) it was not included. Theses and dissertations were involved as well to reduce the chance of publication bias. If a study met the criterias but did not report the zero-order correlations, an email was sent to the corresponding author for the information.

Data Extraction

The coding procedure for the primary studies' characteristics was designed to ensure the extraction of the required data. The two researchers separately extracted the information of the primary studies into a Microsoft Excel spreadsheet. If any disagreements arose, the third researcher, who is an experienced statistician, was involved for resolvement. The following information was coded:

1. Required data including the author name, publication year, sample size, and correlation coefficient of PU-BI, PEOU-BI, and SI-BI.
2. Continuous variables for moderator analysis including mean age of the sample and gender ratio
3. Categorical variables for moderator analysis including region the study was conducted, type of healthcare technology, and presence of technology demonstration

The average age was calculated using frequency counts in age-stratified data or directly extracted from the studies if provided. Geographic region was coded based on the location of the sample collection. The gender ratio was determined by dividing the number of male participants by the number of female participants. Technology domains were categorized into four distinct groups: Mhealth (mobile health apps, mobile health services, etc.), wearable (smart clothing, smart watches, etc.), online and telemedicine (online health platforms, remote consultations, etc.), and home and institutional health hardware (fall monitoring systems, self-service health kiosks, etc.). The presence of technology demonstrations in the studies, whether through a video or live demonstration just prior to the survey or experiment, was recorded as a binary variable.

Quality Assessment

Two reviewers independently assessed the methodological quality of studies using the Newcastle Ottawa Scale. The Newcastle Ottawa Scale uses a star system to evaluate the methodological quality of studies. The adapted cross-sectional tool assigns up to 8 points across three domains: (1) selection of study groups (up to 4 points), (2) comparability of the groups based on age and sex (up to 2 points), and (3) assessment of outcomes (up to 2 points). For this study, it was adapted to properly evaluate TAM and UTAUT-related studies. The ascertainment of exposure was evaluated based on the use of surveys, with a score of 1 if surveys were used and 0 if no information was given. The comparability domain assessed control for age and sex, with 2 points if both were controlled, 1 point if one was controlled, and 0 points if neither were controlled. The assessment of outcomes was based on the use of validated surveys and the reporting of Cronbach's alpha, with 2 points if both were provided, 1 point if only the validated survey was used, and 0 points if neither were described.

Data Synthesis and Analysis

Data was synthesized according to the review objectives.

Objective 1: Synthesize the sample size weighted average of the PU-BI, PEOU-BI, and SI-BI relationships for the current literature.

To pool the effect sizes, random effects analysis was used to calculate the sample size-weighted correlation of the PU-BI, PEOU-BI, and SI-BI relationships. To pool the effect sizes, random effects analysis was used instead of a fixed effects analysis because it accounts for variance that is not just from sampling error but differences in population, methodology, and setting [29]. While the fixed effects model offers a more intuitive method of assigning weights that is solely based on sample size of the study [30], the variations of TAM and UTAUT studies makes the random effects model more suitable. It was conducted through R using the "meta" package which contains functions that make it easy to run different types of meta-analyses [31]. To address potential publication bias, funnel plots were generated through the “meta” package, providing a visual means to detect systematic bias in the meta-analysis. The trim-and-fill method was then applied to adjust for any detected bias, ensuring the pooled effect size was representative and robust. This method is able to account for “missing” effects that may arise from publication bias to correct for small-study effects for the pooled effect sizes [32].

In summary, the study reported the sample size-weighted average of the three pairwise relationships, their 95% confidence intervals, the adjusted weighted averages, and the adjusted 95% intervals.

Objective 2: Identify sources of systematic heterogeneity by analyzing the characteristics of the primary studies that moderate the PU-BI, PEOU-BI, and SI-BI relationships.

Meta-regression was utilized to explore the impact of the continuous moderators age and gender on the three pairwise relationships. The significance level for the beta coefficients was considered at $P < 0.05$. Subgroup analysis was used for the categorical moderators region, technology domain, and presence of visual demonstration on the three pairwise relationships. A Q-test was conducted to measure the heterogeneity between the subgroups and the difference was considered significant at $P < .05$.

Results

Study Selection

The literature search process yielded 1,167 studies (Figure 1). After the removal of duplicates, 928 studies remained for the full-text screening. After assessing the full-text articles for eligibility, the resulting number of studies included in the meta-analysis was 41. There were 2 studies that met the eligibility criteria after additional information was provided by the corresponding author.

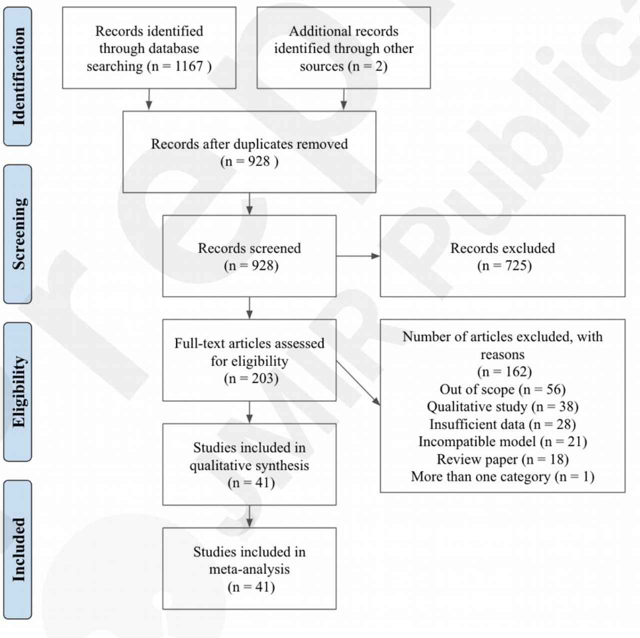

Figure 1: PRISMA flow diagram of evidence search and selection.

Study Characteristics

The summary of the characteristics of the studies is included in Table 1. The total sample size of the primary studies was 11,574. Out of 41 studies, 33 included the mean age of the participants with a total average of 67.58 years. 36 studies reported the gender distribution of their samples, the total ratio being 2.00, with more female participants than male. For each technology type, there were 9 for Wearable, 12 for MHealth, 12 for Online / Telemedicine, and 8 for Home / Institution Hardware. 23 of the studies were conducted in Asia, 7 in Europe, 4 in the United States, and 7 in African-Islamic countries. The description of the studies is included in Table 2.

Table 1: Characteristics of Primary Studies

Author and year	Sample size	Mean age	Gender ratio	Tech type	Region	Visual demonstration
Akhter & Hossain, 2022 [33]	112	57.86	0.87	Mhealth	African-Islamic	No
Alsswey et al, 2019 [34]	81	63.48	0.35	Mhealth	African-Islamic	No
Boontarig et al, 2012 [35]	31	NA	NA	Online Telemedicine	Asia	No
Cimperman et al, 2016 [36]	400	61.13	1.03	Online Telemedicine	Europe	No
Cristescu et al, 2022 [37]	750	NA	NA	Wearable	Europe	No
Diño & de Guzman, 2014 [38]	82	NA	2.57	Online Telemedicine	Asia	No
Etemad-Sajadi & Gomes Dos Santos, 2019 [39]	213	82.1	2.60	Home/Institution Hardware	Europe	No
Greer & Abel, 2022 [40]	30	66.3	NA	Mhealth	United States	No
Hoque & Sorwar, 2017 [41]	274	68.06	0.51	Mhealth	African-Islamic	No
Hsiao & Tang, 2015 [42]	338	67.12	1.08	Wearable	Asia	Yes
Jeng et al, 2022 [43]	166	67.81	1.24	Wearable	Asia	Yes
Khan et al, 2022 [24]	286	NA	0.74	Mhealth	African-Islamic	Yes
Kim et al, 2022 [44]	269	76.1	1.10	Home/Institution Hardware	Asia	No
Koo et al, 2023 [45]	477	64.31	0.73	Mhealth	Asia	Yes
Li et al, 2018 [46]	146	67.41	0.78	Wearable	Asia	Yes
Li et al, 2021 [47]	353	70.38	1.37	Online Telemedicine	Asia	No
Li et al, 2023 [19]	402	NA	0.61	Online Telemedicine	Asia	No
Lu & Tsai-Lin, 2024 [13]	510	75.13	4.15	Online Telemedicine	Asia	No
Ma, 2023 [48]	1318	63.98	0.89	Mhealth	Asia	No
Mahmood & Lee, 2021 [49]	376	70	1.56	Wearable	United States	Yes
Mascret & Temprado, 2023 [50]	230	66.61	2.03	Home/Institution Hardware	Europe	Yes
Mascret et al, 2020 [51]	271	73.69	1.71	Home/Institution Hardware	Europe	Yes
Maswadi et al, 2022 [15]	486	70.80	1.59	Home/Institution Hardware	African-Islamic	No
Mukherjee, 2021 [52]	200	70.75	1.53	Online Telemedicine	United States	No
Pal, 2018 [53]	239	67.14	0.52	Home/Institution Hardware	Asia	No
Palas et al, 2022 [14]	493	66.33	0.18	Mhealth	African-Islamic	No
Pate, 2022 [54]	128	NA	NA	Wearable	United States	No
Pywell, 2021 [55]	313	63.89	1.52	Mhealth	Europe	No
Quaosar et al, 2018	245			Mhealth	African-	No

[56]					Islamic	
Ren & Zhou, 2023 [57]	200	68.83	1.33	Online Telemedicine	Asia	No
Rój, 2022 [58]	400	64.5	1.17	Online Telemedicine	Europe	Yes
Talukder et al, 2020 [59]	325	67.89	0.56	Wearable	Asia	No
Techatraiphum et al, 2016 [60]	45	NA	NA	Online Telemedicine	Asia	No
Tsai, 2020 [61]	81	69.7	0.89	Wearable	Asia	Yes
Tu & Liu, 2021 [62]	487	67.11	1.99	Online Telemedicine	Asia	No
Wang et al, 2023 [63]	365	67.31	1.28	Mhealth	Asia	Yes
Wong et al, 2014 [64]	98	64.93	1	Online Telemedicine	Asia	No
Wu et al, 2023 [65]	78	61.78	1.69	Home/Institution Hardware	Asia	Yes
Xu et al, 2022 [66]	51	68.96	1.32	Home/Institution Hardware	Asia	Yes
Zhang, 2023 [67]	55	59.9	0.67	Mhealth	Asia	No
Zin et al, 2023 [68]	170	68.85	1.27	Wearable	Asia	No

Table 2: Description of the Characteristics of Primary Studies

Characteristics	Statistical Results
Number of studies	41
Total sample size	11,574
Average age	67.58 (SD = 4.76)
Gender	1.26 (SD = 4.52)
- F:M > 1	22
- F:M =< 1	13
Technology Type	
- Wearable	9
- Mhealth	12
- Online / Telemedicine	12
- Home / Institution Hardware	8
Region	
- Asia	23
- Europe	7
- United States	4
- African-Islamic	7

Analysis Characteristics

From the total 41 studies, most studies did not end with just a correlation analysis but conducted more in depth statistical methods such as structural equation modeling and multivariate regression. Although all the correlation coefficients were positive, certain studies reported path coefficients that were not statistically significant or did not have the exact pathway in their final model. The rate at which the correlation coefficient represents the final reportings of the studies is given in Table 3. For the PU-BI relationship, 41 correlation coefficients were extracted from a correlation matrix given in the study. Out of the 41 studies, 31 had the PU->BI path analysis, 27 of which were significant and positive with a rate of 87%. For the PEOU-BI relationship, 41 correlation coefficients were extracted. Out of the 41, 28 included the PEOU-BI path analysis, 21 of which were positive and significant with a rate of 75%. For the SI-BI relationship, 28 correlation coefficients were extracted. Out of the 28, 21 included the SI-BI path analysis, 16 of which were positive and significant with a rate of 76%.

Table 3: Representativeness of final path analysis by correlation coefficient

Pairwise relationship	Frequency of correlation analysis	Frequency of path analysis	Frequency of significant path analysis	Rate of significant path analysis
PU-BI	41	31	27	87%
PEOU-BI	41	28	21	75%
SI-BI	28	21	16	76%

Quality Assessment

Of the 41 studies, the majority were assessed to be of ‘satisfactory’ quality (n=27). A few studies were considered to be of ‘good’ quality (n=14). No studies were assessed as ‘very good’ quality or ‘unsatisfactory’ quality. Quality assessment results (Table 4) for these studies are summarized in the following sections.

Selection

In the selection domain, the studies demonstrated varied results. A small number of studies (n=10) had representative samples, with most studies (n=37) applying convenience or purposive sampling to gain an unrepresentative sample. Around half of the studies (n=20) provided adequate sample size, either with a sample size over 400 or by providing justification for their size. Less than half (n=19) studies had a response rate over 80%, while 18 studies did not provide sufficient details and 4 studies had a response rate less than 80%. All studies were given one star for the ascertainment of exposure since the information was obtained through surveys.

Comparability

Regarding comparability, all studies were given zero stars in this domain. This is because, while some studies did control for age or gender through structural equation modeling (SEM) or multivariate regression, the information used in this analysis was based on correlation coefficients before these controls were applied.

Outcome

In the outcome domain, all studies were given the maximum score of two stars for the assessment of the outcome. Specifically, all 41 studies (n=41) used validated questionnaires from previous TAM and UTAUT studies and reported Cronbach's alpha values, which demonstrated the reliability of the measures. This consistent use of validated measures and reliability reporting supports the overall credibility of the outcome data.

Study	Selection				Comparability	Outcome		Quality Score
	Representativeness	Sample size	Non-respondents	Ascertainment of the exposure	Confounding factors controlled	Assessment of outcome	Statistical test	
Akhter & Hossain, 2022	0	1	Unsure	1	0	1	1	Satisfactory

Alsswey et al, 2020	0	Unsure	1	1	0	1	1	Satisfactory
Boontarig et al, 2012	Unsure	0	Unsure	1	0	1	1	Satisfactory
Cimperman et al, 2016	1	1	Unsure	1	0	1	1	Good
Cristescu et al, 2022	Unsure	1	Unsure	1	0	1	1	Satisfactory
Diño & de Guzman, 2014	0	0	Unsure	1	0	1	1	Satisfactory
Etemad-Sajadi & Gomes Dos Santos, 2019	0	0	0	1	0	1	1	Satisfactory
Greer & Abel, 2022	0	0	Unsure	1	0	1	1	Satisfactory
Hoque & Sorwar, 2017	1	1	1	1	0	1	1	Good
Hsiao & Tang, 2015	1	0	1	1	0	1	1	Good
Jeng et al, 2022	0	0	1	1	0	1	1	Satisfactory
Khan et al, 2022	0	0	1	1	0	1	1	Satisfactory
Kim et al, 2022	0	0	1	1	0	1	1	Satisfactory
Koo et al, 2023	0	1	1	1	0	1	1	Good
Li et al, 2018	0	0	Unsure	1	0	1	1	Satisfactory
Li et al, 2021	0	1	1	1	0	1	1	Good
Li et al, 2023	0	1	Unsure	1	0	1	1	Satisfactory
Lu & Tsai-Lin, 2024	1	1	1	1	0	1	1	Good
Ma & Luo, 2023	0	1	0	1	0	1	1	Satisfactory
Mahmood & Lee, 2021	1	0	Unsure	1	0	1	1	Satisfactory
Mascret & Temprado, 2023	0	0	Unsure	1	0	1	1	Satisfactory
Mascret et al, 2020	1	1	0	1	0	1	1	Good
Maswadi et al, 2022	1	1	Unsure	1	0	1	1	Good
Mukherjee, 2021	0	1	Unsure	1	0	1	1	Satisfactory
Pal et al ,	0	0	1	1	0	1	1	Satisfac

2018								tory
Palas et al, 2022	1	1	1	1	0	1	1	Good
Pate, 2022	0	1	1	1	0	1	1	Good
Pywell, 2021	0	1	1	1	0	1	1	Good
Quaosar et al, 2018	0	0	1	1	0	1	1	Satisfactory
Ren & Zhou, 2023	1	0	1	1	0	1	1	Good
Rój, 2022	1	1	Unsure	1	0	1	1	Good
Talukder et al, 2020	0	0	1	1	0	1	1	Satisfactory
Techatraiphum et al, 2016	0	0	1	1	0	1	1	Satisfactory
Tsai, 2020	0	0	Unsure	1	0	1	1	Satisfactory
Tu & Liu, 2021	0	1	1	1	0	1	1	Good
Wang et al, 2023	Unsure	1	1	1	0	1	1	Good
Wong et al, 2014	Unsure	Unsure	Unsure	1	0	1	1	Satisfactory
Wu et al, 2023	0	Unsure	Unsure	1	0	1	1	Satisfactory
Xu et al, 2022	0	Unsure	Unsure	1	0	1	1	Satisfactory
Zhang, 2023	0	1	0	1	0	1	1	Satisfactory
Zin et al, 2023	0	1	Unsure	1	0	1	1	Satisfactory

Notes: Very good studies: 7-8 points, Good studies: 5-6 points, Satisfactory studies:3-4 points, Unsatisfactory studies: 0-2 points

Effect Sizes and Publication Bias Adjustment

The weighted average of the correlations of the three pairwise relationships, PU-BI ($r = 0.607$, 95% CI 0.543 − 0.665, $P < 0.001$), PEOU-BI ($r = 0.525$, 95% CI 0.462 − 0.583, $P < 0.001$), and SI-BI ($r = 0.551$, 95% CI 0.468−0.624, $P < 0.001$), was calculated using the random effects model. The confidence interval of each effect indicated a positive relationship for the intention to accept technology. The heterogeneity was calculated through a Q test and an I2 test for PU-BI ($Q = 973.77$, $df = 40$, $P < 0.001$, $I^2 = 95.9\%$), PEOU-BI ($Q = 626.95$, $df = 40$, $P < 0.001$, $I^2 = 93.6\%$), and SI-BI ($Q = 580.59$, $df = 27$, $P < 0.001$, $I^2 = 95.3\%$), all of which showed a high degree of heterogeneity. To test the possibility of publication bias, the funnel plot method was utilized to detect any asymmetry. If detected, the trim-and-fill method was utilized to adjust the weighted average of the effect by filling in additional points to maintain symmetry. Among the three relationships, SI-BI required 6 additional point as shown in Figure 2, while the PU-BI and SI-BI required none. The weighted average of the effect sizes and the adjustments after the trim-and-fill are reported in Table 5. The table summarizes the results of the three pairwise relationships through the quantitative synthesis by confirming that each pair has a positive association, meaning that the intention to accept healthcare technology is dependent on the usefulness, ease of use, and social influence.

Pairwise relationship	Total sample size	Weighted correlation	CI (95%)	Adjusted weighted correlation	Adjusted CI
PU-BI	11,574	0.607	0.542 - 0.665	0.607	0.542 - 0.665
PEOU-BI	11,574	0.525	0.462 - 0.583	0.525	0.462 - 0.583
SI-BI	8,264	0.559	0.476 - 0.632	0.471	0.363 - 0.566

Moderator Analysis

Age

Out of the 39 studies, 31 studies were included in the meta-regression with the sample age as its coefficient. One relationship, PU-BI (β = 0.000, *P* = .99) was positively associated with the mean age of the sample while PEOU-BI (β = −0.126, *P* = .19) and SI-BI (β = -0.017, *P* = .35) were negatively associated with age. However, the significance test showed that the results for the three relationships were not significant.

Gender

While 35 primary studies reported the number of female and male participants, one study [40] that involved 29 females and one male was removed as it was deemed an outlier. Therefore, the remaining 34 studies were included in the meta-regression with the female-to-male ratio as its coefficient. PU-BI (β = 0.126, *P* = .07), PEOU-BI (β = 0.037, *P* = .56), and SI-BI (β = 0.105, *P* = .34), were positively associated with the proportions of female participants over the male participants. However, the significance test proved none of the relationships to be significant.

Geographic Region

A subgroup analysis of the geographic regions was conducted to report the effect size of each relationship for each region, the United States, Europe, Asia, and African- Islamic. From highest to lowest in correlation for PU-BI (Q = 6.3, *P* = .10), the order was the United States (r = 0.713), Europe (r = 0.712), Asia (r = 0.572), and African-Islamic (r = 0.529). For PEOU-BI (Q = 8.27, *P* = .4), the order was Europe (r = 0.628), the United States (r = 0.587), Asia (r = 0.492), and African-Islamic (r = 0.480). For SI-BI (Q = 2.63, *P* = .45), the order was the United States (r = 0.700), Europe (r = 0.602), Asia (r = 0.548), and African-Islamic (r = 0.495). After conducting a Q-test, only the PEOU-BI relationship (Figure 2) had a difference in the subgroups large enough to be considered significant.

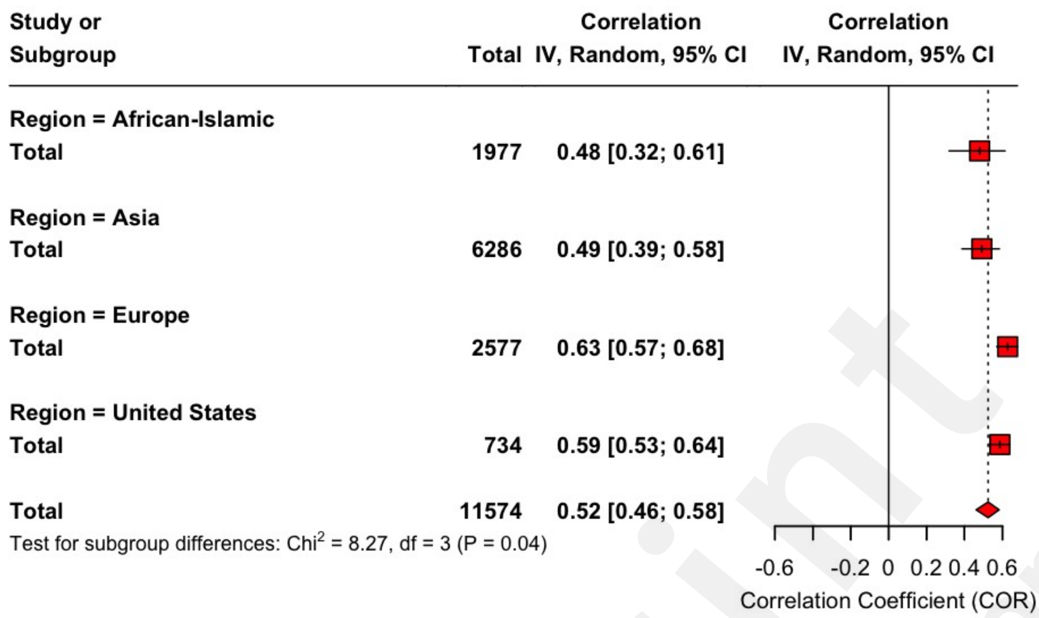

Figure 2: Subgroup analysis of region for PEOU-BI relationship.

Technology Type

All studies were involved in a subgroup analysis of the technology type, which were divided into Wearable, mHealth, Online/Telehealth, and Home/Institutional. For PU-BI (Q = 8.08, *P* = .04), the order from highest to lowest in correlation was Home/Institutional (r = 0.736), Wearable (r = 0.642), Mhealth (r = 0.578), Online/Telehealth (r = 0.501). For PEOU-BI (Q = 4.15, *P* = .25), it was Home/Institutional (r = 0.641), Mhealth (r = 0.510), Online/Telehealth (r = 0.489), and Wearable (r = 0.467). For SI-BI (Q = 14.75, *P* = .002), the order was Home/Institutional (r = 0.690), Wearable (r = 0.664), Mhealth (r = 0.550), and Online/Telehealth (r = 0.415). The Q-test for the PU-BI (Figure 3) and SI-BI (Figure 4) proved the differences in the subgroups to be significant but not for PEOU-BI.

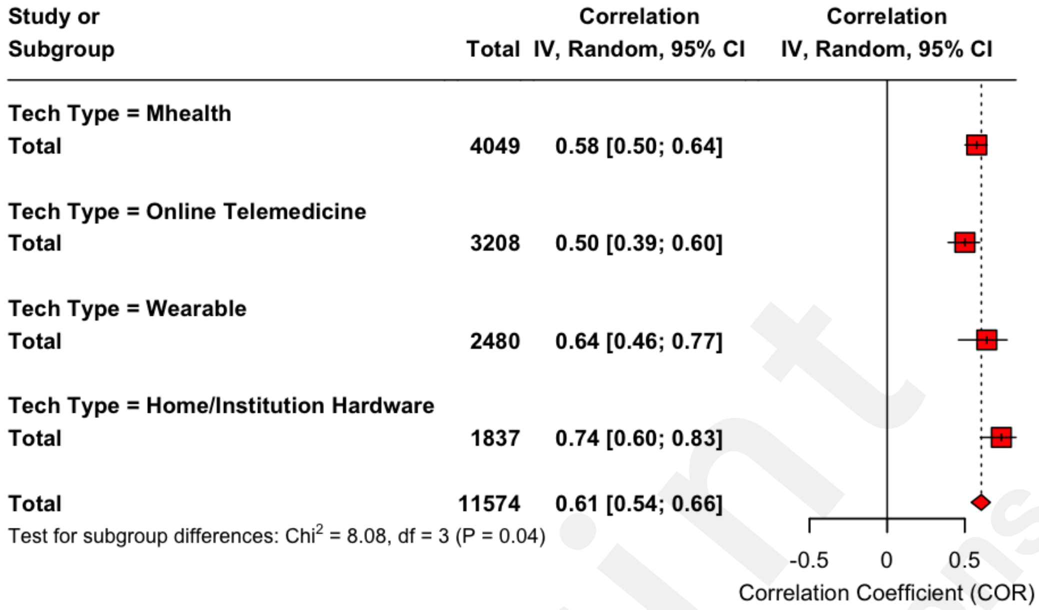

Figure 3: Subgroup analysis of healthcare technology type for PU-BI relationship.

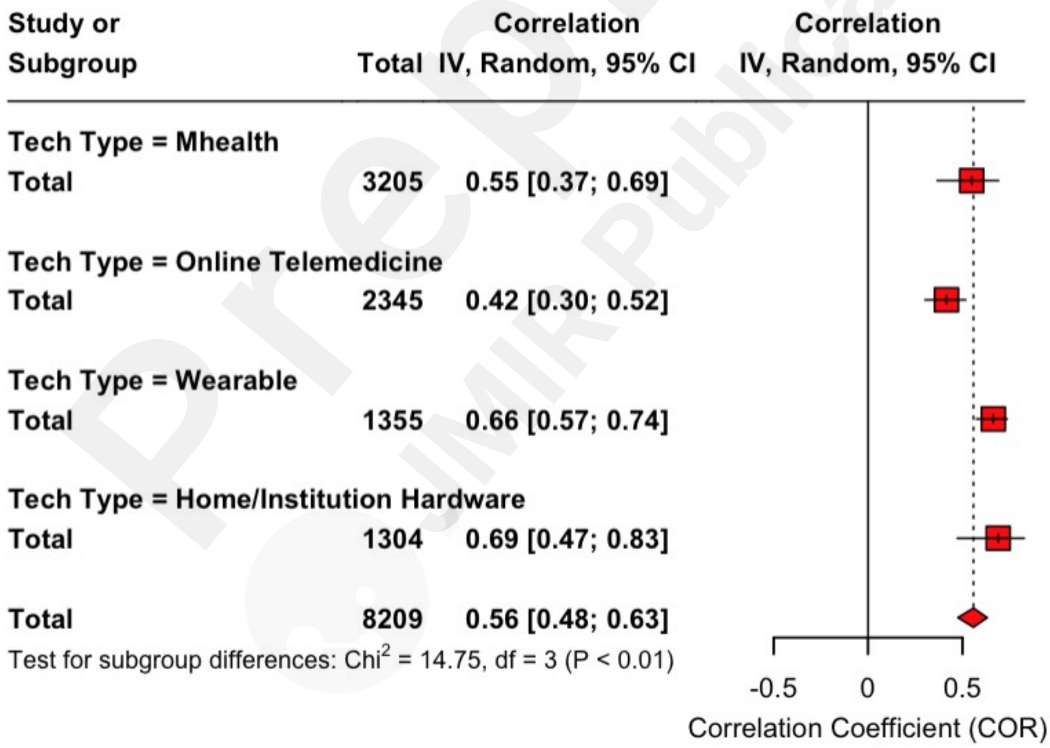

Figure 4: Subgroup analysis of healthcare technology type for SI-BI relationship.

Visual Demonstration

A subgroup analysis was conducted by dividing the studies into two groups, one that involved a visual demonstration of the technology prior to the survey, and one without. For the relationship PU-BI (Q = 4.24, *P* = .04), studies that provided a visual demonstration (r = 0.706) had a higher effect size compared to studies that did not (r = 0.554). For PEOU-BI (Q = .16, *P* = .69), studies that provided a visual demonstration (r = 0.535) displayed a lower effect compared to studies that did not (r = 0.501). Lastly, for SI-BI (Q = 4.38, *P* = .04), studies that provided a visual demonstration (r = 0.670) again displayed a higher effect than studies without (r = 0.492). For PU-BI (Figure 5), and SI-BI (Figure 6), the Q-test proved the significance of their difference while not for PEOU-BI.

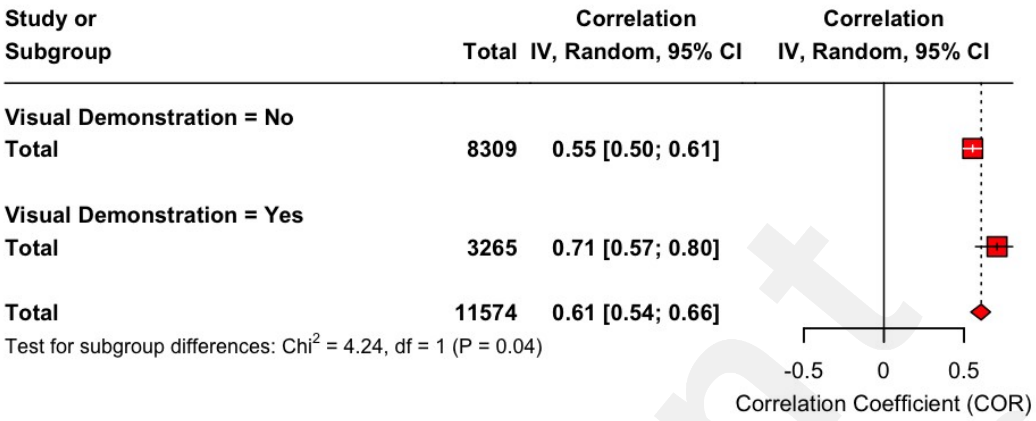

Figure 5: Subgroup analysis of presence of visual demonstration for PU-BI relationship.

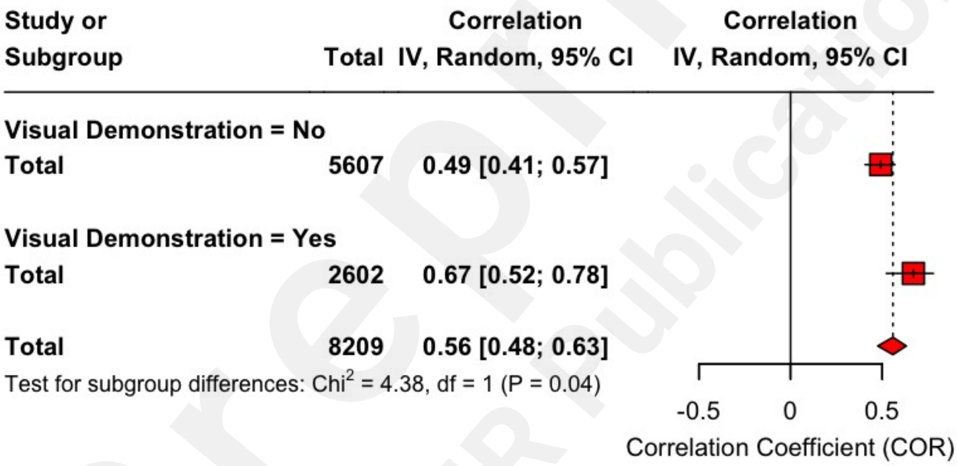

Figure 6: Subgroup analysis of presence of visual demonstration for SI-BI relationship.

Discussions

Overall Effect Sizes

One of the objectives of this meta-analysis was to obtain a comprehensive view of the research landscape regarding the factors influencing the intention to accept healthcare technology among older adults by combining the constructs of TAM and UTAUT into three pairwise relationships. The pooled results of the different studies supported the positive correlations for PU, PEOU, and SI for BI. This suggests that older adults' choice to use healthcare technology is dependent on how useful they perceive it to be for their pursuit of health. While a separate study noted a lower correlation between PU and BI for healthcare technology compared to other types of technology [69], the combined results of different studies suggested a strong correlation still remains. The results also indicated that how easy it seems to use healthcare technology determines older adults' intention to use the technology. Older adults may face cognitive and physical challenges [70, 71] and technologies that are easy to use are more likely to be adopted because they accommodate these limitations, ensuring the technology is accessible to them [72]. Social influence is also important for older adults when accepting healthcare technology. Current research reports the substantial effect of family members, friends, or caregivers on the adoption of healthcare technology [69] and this research's findings support this claim.

Moderator Analysis

Beyond confirming the significant associations of PU, PEOU, and SI with behavioral intention, this research aimed to explain the heterogeneity observed in the current landscape of studies through moderator analysis. Considerable variability in the effect sizes across studies was evident, prompting further investigation through subgroup analysis and meta-regression to identify potential moderators such as age, gender, geographic region, technology type, and the usage of visual demonstrations.

Age

The analysis revealed that the relationships between the constructs and behavioral intention varied slightly with age, though the trends were not sufficient to reach statistical significance. This is in line with the results from Ma et al. that found a lack of moderating effect of age for acceptance of various types of technology, suggesting that a deeper look into healthcare technology reports the same results [28]. In addition, Hauk et al.'s meta-analysis reported that age has a negative effect on TAM constructs unless the technology in question addresses the needs of older individuals, explaining the absence of a moderating effect on healthcare technology [73]. Such results provide a new way of understanding age for technology acceptance that differs from the age stereotypes that assumes a negative effect of age.

Gender

The gender analysis did not show any significant effect on the relationships studied suggesting that gender does not significantly impact the acceptance decisions related to healthcare technology. A review paper concluded that the influence of gender on technology adoption depends on the context and type of technology [74], implying that gender effects may not be relevant in the context of healthcare technology. It is important to note that the primary studies included in this meta-analysis had more female participants than male, which could introduce potential bias. Consequently, the results related to gender should be interpreted with caution, and future research should aim for a more balanced sample to ensure comprehensive understanding of healthcare technology acceptance among older adults.

Geographic Region

Subgroup analysis by geographic region revealed that for PU-BI, the United States and Europe displayed the highest correlations, followed by Asia and African-Islamic regions, indicating that perceived usefulness is more strongly related to behavioral intention in Western cultures. For PEOU-BI, Europe showed the highest correlation, followed by the United States, Asia, and African-Islamic regions. This is in line with the findings of McCoy et al. that reported that the PU-BI and PEOU-BI relationship tends to be weaker for countries that have a higher power distance [75] as the countries in the Asia category (China, Taiwan, Korea) and African-Isalmic category (Bangladesh, Saudi Arabia, Pakistan) report much higher in power distance. Future studies could examine how cultural contexts shape the acceptance and use of healthcare technology for older adults.

Technology Type

The discussion of our results highlights several significant insights into the factors influencing technology adoption among older adults. Notably, Home/Institutional Hardware exhibited the highest correlations for both PU and PEOU. These technologies, which include devices such as smart home systems and health kiosks, are inherently designed to improve quality of life, making their usefulness and user-friendliness paramount to their adoption [76, 44]. In contrast, Online/Telemehealth technologies showed the lowest correlations across PU and SI. This suggests factors such as privacy or trust as identified in other studies [77, 78] may be more critical determinants of acceptance. Another important finding is the high correlation of SI-BI and low correlation of PEOU-BI for wearable technology. This suggests that social proof and endorsements could be powerful tools in promoting wearable technology within this demographic. A possible reason for this is because wearable technology is not perceived as just a healthcare technology but as a fashion accessory [79], which is why production quality and social value are important factors [59]. Overall, these results point to the need for tailored strategies that address specific barriers and leverage unique motivators for different types of technology to enhance adoption rates among older adults.

Visual Demonstration

The significant differences observed in the studies that included visual demonstrations emphasize the crucial role of reducing perceived risk in consumer theory for the acceptance of healthcare technology by older adults. Perceived social risk and physical risk plays an important role when acquiring information about new technology [80] but visual demonstrations can reduce the abstractness and uncertainty surrounding new healthcare technology by providing clear, tangible evidence of its functionality. Specifically for older adults, perception of automated vehicles, such as its perceived usefulness, of older adults improved after an exposure to a simulator and a demonstration in an automated shuttle [81]. Similarly, a practical engagement may solidify the constructs of PU, PEOU, and SI by directly showcasing exactly how the technology works and its practical benefits, thus making other unidentified variables influencing BI less significant.

Limitation

This meta-analysis has several important limitations that should be considered when interpreting the findings. First, the main source of analysis, which is the correlation coefficient of the TAM constructs, were used instead of the finalized path coefficient of the primary studies. While this ensures the comparability and synthesis of the weighted averages of the effect sizes, it may not fully represent the results of the primary studies as the control variables are removed in the correlation analysis. Second, the use of different methods across studies to collect the information has noteworthy limitations. Although most studies obtained their data through online surveys, other methods such as face-to-face distribution, telephone, and mobile surveys were used, making it possible for the possibility of the mode effect. Lastly, because the primary studies were restricted to English, language bias may exist. This restriction may lead to the underrepresentation of valuable research published in languages other than English, limiting the comprehensiveness and global applicability of the findings.

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Conflicts of Interest

None declared.

Abbreviations

JMIR: Journal of Medical Internet Research
RCT: randomized controlled trial

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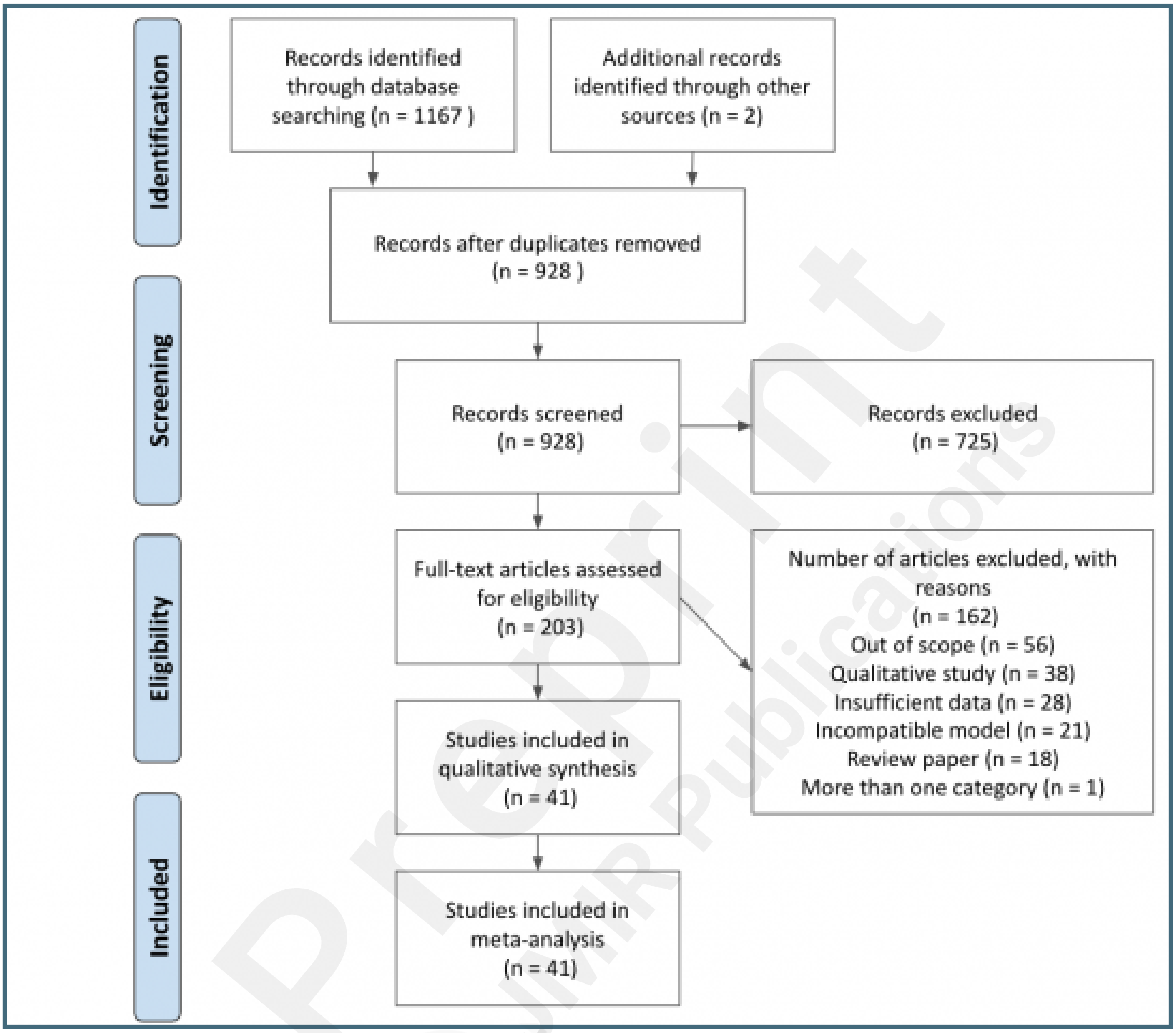
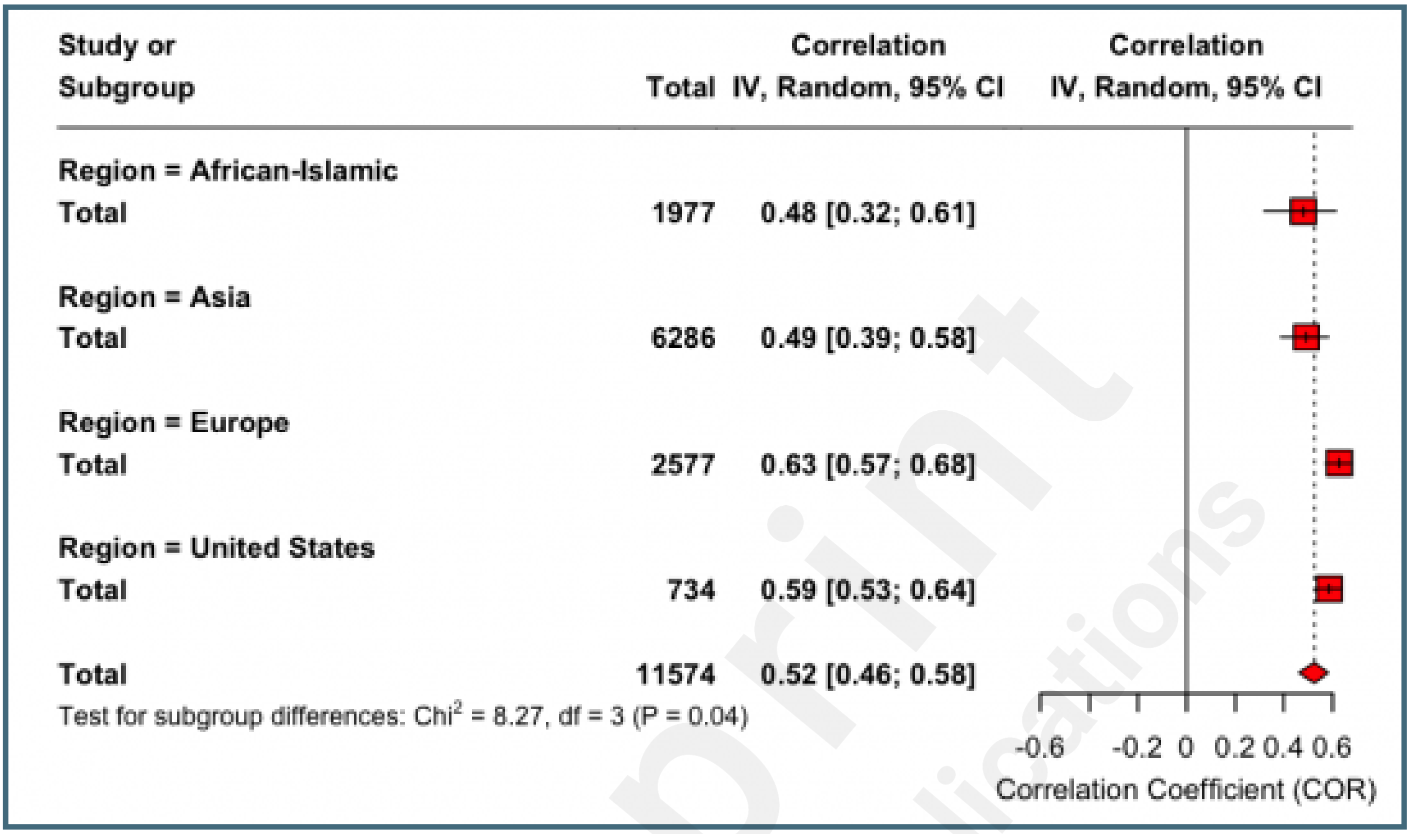
Supplementary Files

Figures

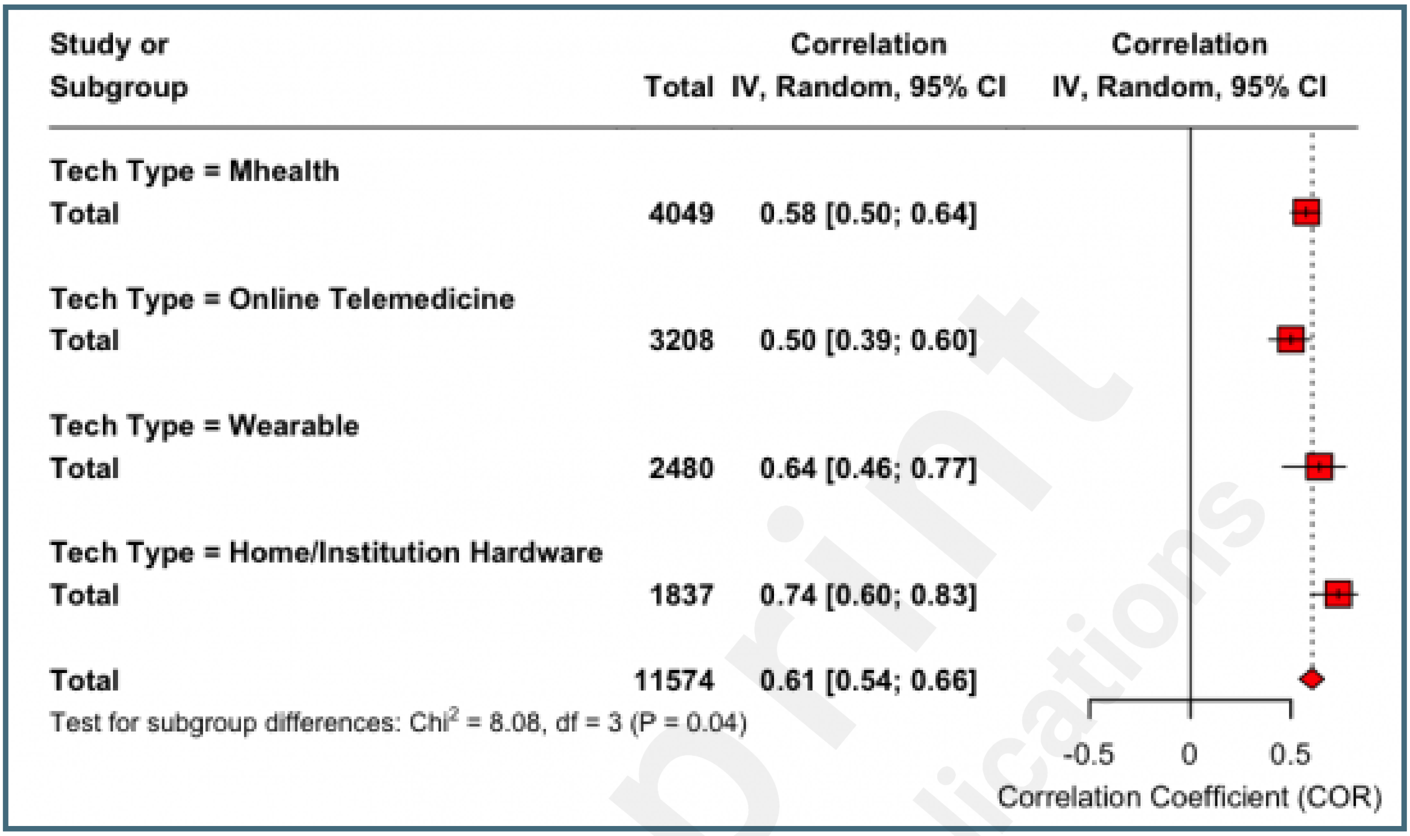
PRISMA flow diagram of evidence search and selection.



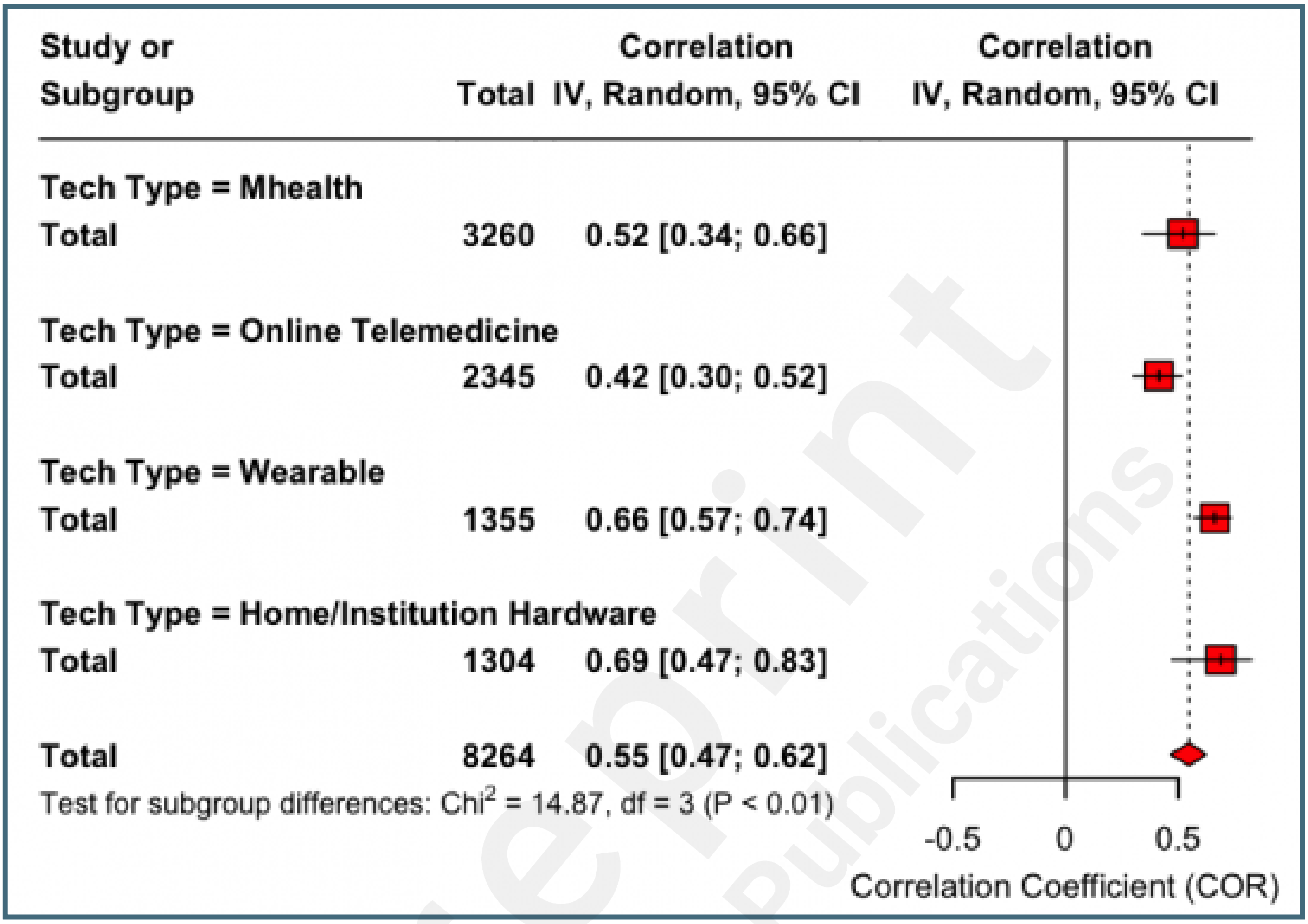
Subgroup analysis of region for PEOU-BI relationship.



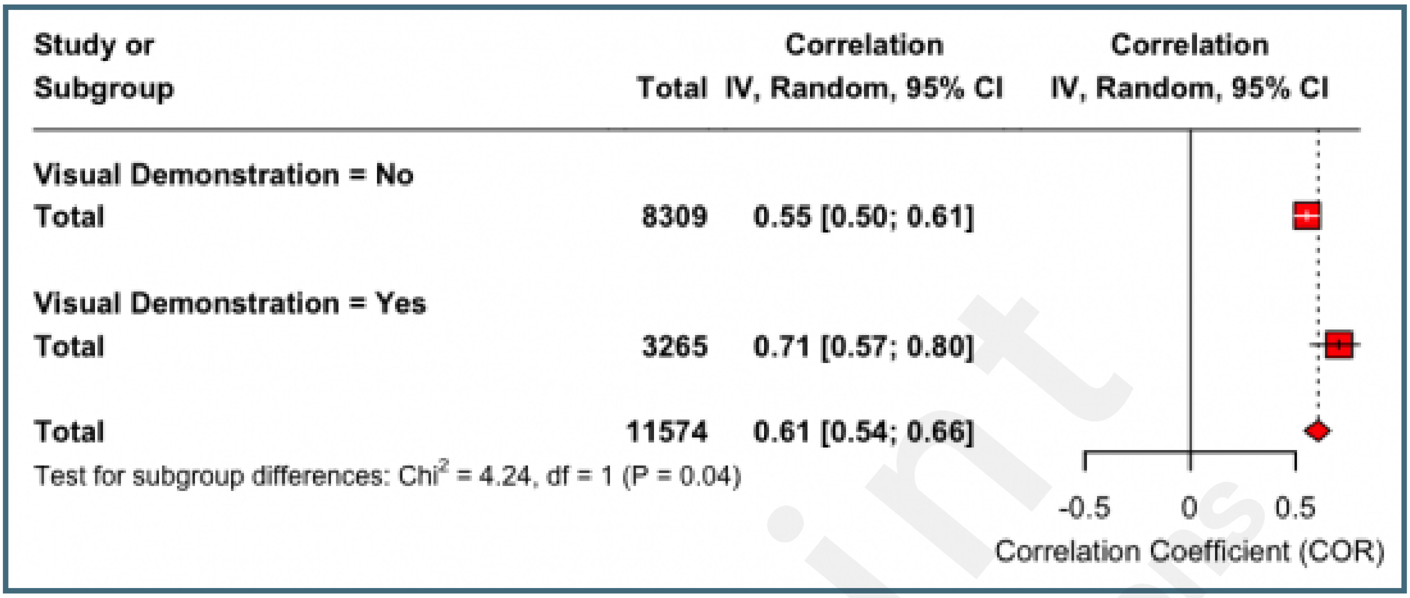
Subgroup analysis of healthcare technology type for PU-BI relationship.



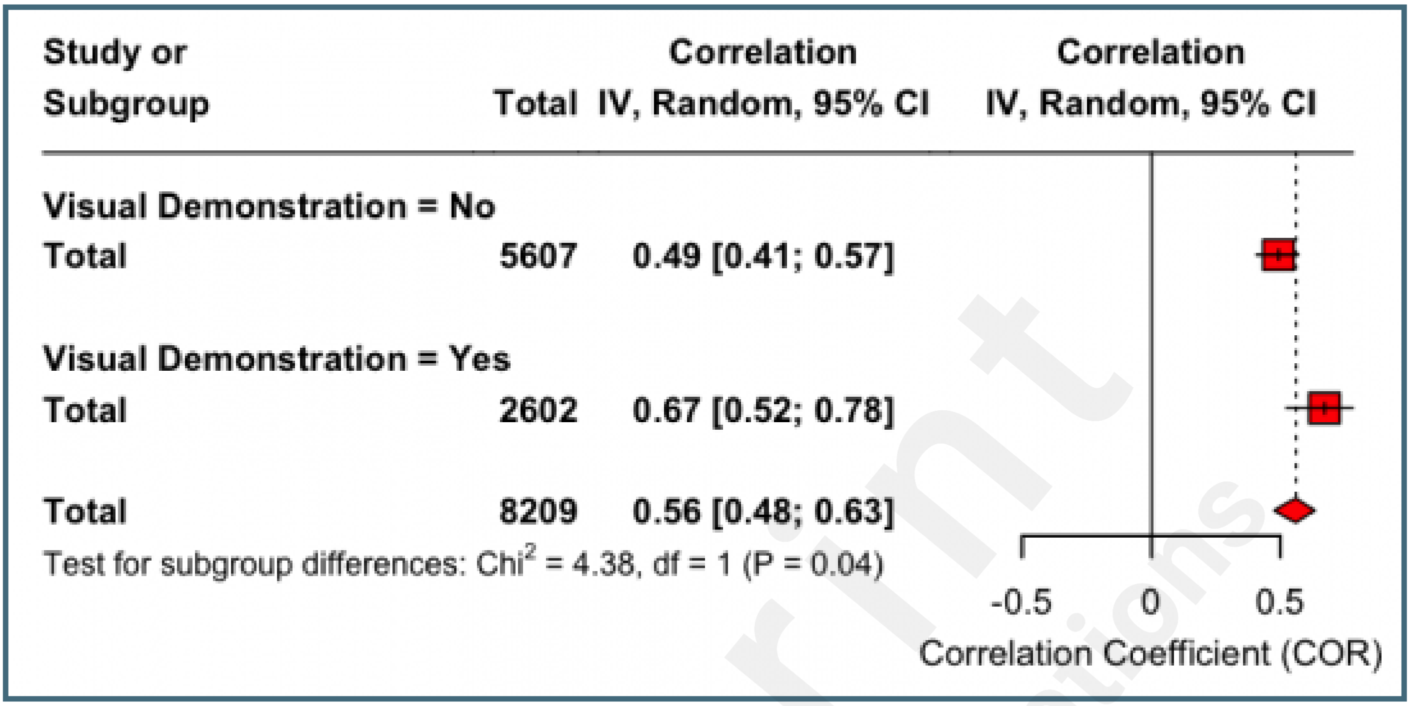
Subgroup analysis of healthcare technology type for SI-BI relationship.



Subgroup analysis of presence of visual demonstration for PU-BI relationship.



Subgroup analysis of presence of visual demonstration for SI-BI relationship.



Multimedia Appendixes

Additional figures of meta-regression and subgroup analysis.
URL: http://asset.jmir.pub/assets/997f2632c2f74d983aa89435b51b55f2.docx

TOC/Feature image for homepages

Older adult using a healthcare technology.