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Exploring the Determinants of Online Health Information-Seeking Behavior Using a Meta-Analytic Approach

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Abstract: Although key factors of online health information-seeking behavior (OHISB), such as self-efficacy, Internet experience, and perceived ease of use, are analyzed in many studies, the research results are controversial. The purpose of this meta-analysis, based on 27 related empirical studies, is to explore the determinants of OHISB. The determinants of OHISB are classified into four categories: demographic characteristic factors, cognitive factors, internal factors, and external factors. According to the results of the analysis using Stata13.0, our study found a weak effect of perceived cost and health anxiety on the OHISB, while subjective norm, perceived usefulness, and attitude have a strong positive effect on the OHISB. Understanding the determinants of OHISB is beneficial in order to know why users utilize online health applications. The findings of the study can contribute to developing and extending the existing theoretical concepts.

Keywords: online health; information seeking; meta-analysis; behavioral analysis

1. Introduction

The advancement of mobile communication and openness of mobile Internet make more and more people turn to mobile devices to obtain several types of information, such as medical and health information. There is a growing awareness of the importance of health, and health information can help determine treatments and provide coping mechanisms for people with chronic diseases [1]. For example, the insurance companies, Tencent, dxy.cn and Zhongan cooperate to integrate the intelligent blood glucose meter into the online health consultation and health management services of dxy.cn to treat diabetes, a chronic disease. Based on the data and measurement habits of patients with diabetes, insurance services for rehabilitation incentives are provided to help patients gradually develop the good habit of scientific sugar control. Therefore, countries around the globe, such as American, France, and other developed countries, are converting the health system from traditional offline setups to online advanced technological setups for better healthcare [2]. Meanwhile, China is actively promoting the development of e-healthcare to improve the level of basic public health services and management as well as the service level of medical institutions. Online health information sharing service platforms can provide a variety of convenient services such as an online appointment, diagnosis and treatment, and telemedicine services for remote areas and small and medium-sized cities, and can improve the ability to prevent and control major diseases and public health emergencies by means of the Internet and big data [3].

Due to health hazards, environmental pollution, work pressure, personal awareness, and other factors, individuals pay more attention to the health of themselves or their relatives. According to iResearch's online health monitoring report (http://report.iresearch.cn), the frequency of use of online health Apps showed a monthly increase trend from January 2015 to December 2015, which

may increase up to 4 billion in 2020. However, as an emerging entity, online health information services still face great challenges in gaining wide recognition and long-term support from the public. Therefore, considering the rapidly growing number of online health users, it is of great significance to understand the key factors of online health information-seeking behavior, which is valued by most scholars for improving users' healthcare. According to information behavior models, the main categories of intervening variables of online health information-seeking behavior (OHISB) include psychological factors, demographic factors, role-related or interpersonal factors and environmental factors [4,5]. Therefore, the key factors, including 17 variables in this meta-analysis, are classified into four parts based on this categorization method. The first part is the demographic characteristic variables, which involve age, education, income, and gender. The second part refers to cognitive factors, which are defined by the users making decisions based on the perception of things and reflect users cognitive and emotional characteristics, as mentioned in previous studies, including perceived usefulness, perceived ease of use, perceived behavioral control, perceived risk, perceived benefit and perceived cost [5]. The third category is internal factors that reflect the impact of differences in individual characteristics of consumers on OHISB, containing self-efficacy, attitude, Internet experience, health anxiety, and trust. The last are external factors, which refer to the influence of the external environment on users' behavior, including social support and subjective norm.

Many researchers looked at health information-seeking behavior based on Internet technology [6–9]. These scholars have investigated the relationship between and the effect of demographic characteristic variables, cognitive factors, internal factors, external factors, and OHISB. Specifically, based on a comprehensive model of information seeking, the older the family caregivers are, the less likely they are to conduct OHISB [10]. Several studies argued that self-efficacy is positively associated with OHISB [2,8,9,11,12]. The impact of health anxiety, gender, and Internet experience are significantly positively associated with OHISB [8].The association between information, social support, and OHISB are positive [9]. The perceived benefits, including learning benefits, functional benefits, social benefits, and personal integrative benefits, can promote OHISB [1].

However, other studies produced inconsistent results. The effect of age on OHISB has been verified to have small significant. Some researchers argue the opposite view, that self-efficacy had a negative relationship to OHISB [13,14]. People with poor health conditions are not willing to share, offer, or discuss their health information on the Internet [15]. This indicates that there is a negative relationship between health anxiety and OHISB. The effect of gender differences on OHISB is minimal [9]. The perceived benefits have a medium effect rather than a very strong effect on health-related behavior [16].

As these studies show mixed results, the effect of influencing factors on OHISB is ambiguous. Therefore, this study is important to fill the existing gap in the literature by executing a meta-analysis on the existing literature that will develop a comprehensive understanding this particular issue.

To date, the method of the meta-analysis was just applied to research on the influencing factors of online health service adoption and has not been applied to research on the effects of the influencing factors on OHISB [17]. Due to the influence of research objects, research samples, and other factors, it is normal to have differences in research results of OHISB. Therefore, this study adopts the meta-analysis method to form a comprehensive analysis of the determinants of OHISB based on the results of different studies.

2. Materials and Methods

2.1. Literature Search Strategy

This meta-analysis followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, which is a tool to evaluate the quality of the selected studies [18]. The retrieval of the literature was mainly carried out in the following synthesis databases and general databases: Web of Science, Google Scholar, Ebsco, Elsevier, Emerald, Springer, and Taylor & Francis. The time

span of the studies published or available online was from January 2012 to April 2019. We searched by the combination of the following keywords: "Internet Health", "online health", "mobile health", "m-health", "e-health", and "Information Seeking".

2.2. Selection Criteria for Sample Data and Quality Assessment

The selection criteria for the study were as follows: (1) The studies had to be a quantitative study of OHISB, excluding theoretical research, review papers, comment, etc.; (2) The studies had to contain explicit or convertible correlation affect values, such as correlation coefficient, t value, F-value, path coefficient, and correlation matrix; (3) If multiple studies using the same research sample for empirical analysis were found, only one of them was taken for analysis; (4) The studies were published in English; (5) The sample size had to be clear; (6) The studies had to include at least one of the relationships of the effect of factors on OHISB. The flow diagram of literature retrieval and screening is shown in Figure 1. First, we used the database to retrieve 221 relevant records. After deleting the duplicated studies, there were 121 unique studies. By scanning the title or abstract, we narrowed the record down to 79. In order to ensure the accuracy of the research results, two authors further screened the full text according to the inclusion criteria and obtained a total of 41 studies. Finally, 14 articles were excluded for reasons such as the lack of important data. AMSTAR 2 (Assessment of Multiple Systematic Reviews) is a modified AMSTAR criteria, which is an update of the original AMSTAR, used to assess the methodological quality of systematic reviews [19]. Two investigators independently assessed the quality of the selected study, according to AMSTAR 2, as high (score range: 12–16), moderate (score range: 9–11), low (score range: 5–8), or critically low (score range: 0–4) [20]. If there was any disagreement, the two sides made the final decision through discussion. Therefore, 27 articles were used for meta-analysis.

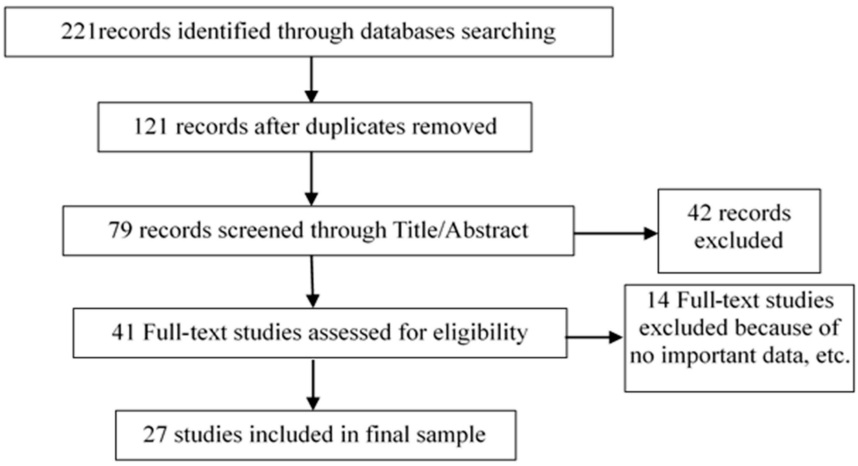


Figure 1. Studies selection flow diagram.

Data Collection and Coding

This study was carried out in strict accordance with the coding steps recommended by Lipsey and Wilson [21], with two students coding independently and forming a coding table. The coded data included the description item of the published information and research conclusion. Published information included author, year published, and publication name, and the conclusions covered the sample size and effect value required for the meta-analysis. The correlation coefficient was usually used as the evaluation index for the effect size of the meta-analysis. It can also be converted into a correlation coefficient based on t value, F-value, and other statistics. Therefore, we mainly took the correlation coefficient as the effective value of this study. After the first coding, the two students cross-checked the information and dealt with the inconsistent coding content through the correcting of errors and by negotiation. If the variables were measured by multidimensional terms in the same

sample number, the simple average was calculated as the final effect value. If the sample size was inconsistent, the effect value of the variable was taken as the new research object. The selected studies for doing meta-analysis are presented in Table 1.

Table 1. Selected Studies for Meta-analysis.

Publication	Impact Factor	Year of Publication	Country	Group	Sample Sizes
Ren [1]	1.179	2019	South Africa	Undergraduate	282
Ahadzade et al. [22]	1.928	2016	Malaysia	Malaysian females	270
Basnyat et al. [6]	1.773	2018	India	Population	990
Cao et al. [12]	1.846	2016	China	Population	393
Chang [7]	2.65	2015	China	Students	3234
Kim et al. [23]	4.896	2013	USA	Patients	271
Lagoe [8]	4.306	2015	USA	Adults	245
Lee & Lin [24]	1.773	2016	India	Population	993
Li [25]	2.297	2015	USA	Patients	3014
Li et al. [26]	3.815	2018	China	Undergraduate	156
Lin et al. [15]	4.306	2016	USA, South Korea, Hong Kong	College students	789
McKinley & Wright [9]	4.306	2014	USA	Undergraduate	297
Miller & Bell [27]	2.007	2012	USA	Adults	3796
Myrick [28]	4.306	2017	USA	Population	375
Oh [10]	1.097	2015	USA	Patients	1113
Oh & Song [29]	1.029	2017	Korea	Adults	2351
Walsh et al. [30]	1.932	2015	Australia	Parents	391
Xitong Guo et al. [31]	3.553	2013	China	Patients	204
Jaafar et al. [2]	2.731	2017	Malaysia	Patients	271
Deng [32]	2.731	2017	China	Patients or their family members	436
Johnston et al. [33]	1.263	2013	USA	Patients	153
Mou [16]	1.263	2016	South Africa	Undergraduate	703
Sun et al. [11]	1.786	2013	China	Patients	204
Rains & Tukachinsky [13]	1.773	2015	USA	Undergraduate students	162
Ruppel [34]	1.773	2015	USA	Patients	3315
Zhang et al. [35]	0.787	2014	China	Population	491
Zhang et al. [36]	1.996	2014	China	Population	481

2.3. Meta-Analysis and Effect Size Calculations

The meta-analysis software used in this study was Stata 13.0, which is used to examine publication bias, heterogeneity, and to calculate combined effect sizes. Publication bias was tested according to Fail safe N. When the ratio between Fail-safe N and 5K + 10 is greater than 1, and the result is robust. The quantitative statistical methods of heterogeneity were mainly evaluated according to Q tests and I2 statistics [37]. When the Q statistic is greater than k − 1 (k is the number of independent studies), and the p value reaches the significance level, it can be considered as heterogeneous. I2 statistics reflect the difference caused by the heterogeneity of the effect values. If the distribution of effect value is heterogeneous (Q > k−1, I2 > 0.5 and p < 0.10), the random effect model is adopted; otherwise, the fixed-effect model is adopted. The effect size is the value that quantifies the strength of the influencing factors of OHISB and can represent the magnitude (small, medium, or large) and direction (positive or negative). The combined effect values are shown as follows, according to Hunter and Schmidt' meta-analysis technique [38]:

$$\text{Fisher's } Z_i = 0.5 \times Ln\frac{1+r_i}{1-r_i}$$
$$\text{Fisher's } Z_+ = \frac{\sum n_i Z_i}{\sum n_i}$$
$$r_z = \frac{e^{2\times Fisher'sZ_+}-1}{e^{2\times Fisher'sZ_+}+1}$$

where r_i is the correlation coefficient reported in independent study, n_i is the sample size corresponding to the effect value of the study i, and r_z is the final modified effect size after statistical combination for each factor of OHISB.

The 95% confidence interval (CI) of effect size (r) is calculated as follows:

$$Upper\ limit = r_m + 1.96 \times \text{s.d.}$$
$$Upper\ limit = r_m + 1.96 \times \text{s.d.} Lower\ limit = r_m - 1.96 \times \text{s.d.}$$

where s.d. is the standard deviation and r_m is the mean effect size for each pair-wise relationship.

If the correlation coefficient is not reported, the path coefficient can be directly treated as the correlation coefficient, or the t statistic can be indirectly converted into the correlation coefficient, calculated as follows:

$$r_i = \sqrt{\frac{t^2}{t^2 + df}}$$

where t = t-statistic, $df = n - 1$, df is the degrees of freedom, and n is the number of independent studies.

3. Results

3.1. Characteristics of the Studies

Our meta-analysis included 27 studies that examined the effect of determinants on OHISB; the research papers were published between 2012 and 2019. A total of 25,380 students, patients, and other groups participated in the studies. Twenty-nine studies were conducted in the United States, China, India, Malaysia, South Korea, South Africa, and Australia. The largest number of OHISB studies was performed in the USA, followed by China, with only one or two studies in other countries. In terms of the study group, the subjects of the study were mainly patients or their family members, undergraduate students, or the general population. The minimum number of samples was 153, and the maximum was 3796.

3.2. Meta-Analysis

Based on existing research, we classified the determinants by aligning them with demographic characteristics, cognitive factors, internal factors, and external factors. Demographic characteristic factors included age, income, education, and gender. The cognitive factors were usefulness, perceived ease of use, perceived behavioral control, perceived risk, perceived benefit, and perceived cost. Internal factors were composed of self-efficacy, attitude, Internet experience, health anxiety, and trust, and external factors included social support and subjective norm.

3.2.1. Publication Bias Analysis

To test for publication bias, fail-safe N was calculated in this study and is presented in Table 2. When fail-safe N is less than 5K + 10, publication bias should be paid attention to [39]. As shown in Table 2, Fail-safe N/5k + 10 of each pair-wise relationship is larger than 2, which indicates that there is no publication bias in this study.

Table 2. Analysis result of reporting bias.

Variable.		Fail-safe N	5k + 10	Fail-safe N/5k + 10	*p*. Bias Risk
Demographic Characteristics	Age	1260.82	50	25.22	low
	Income	198.24	40	4.96	low
	Education	986.19	50	19.72	low
	Gender	915.98	45	20.36	low
Cognitive Factors	Perceived usefulness	938.17	40	23.45	low
	Perceived Ease of Use	227.51	30	7.58	low
	Perceived behavioral control	91.55	25	3.66	low
	Perceived risk	683.32	35	19.52	low
	Perceived benefit	1212.52	45	26.94	low
	Perceived cost	58.25	25	2.33	low
Internal Factors	Self-efficacy	642.37	55	11.68	low
	Attitude	893.82	35	25.54	low
	Internet experience	4989.9	50	99.80	low
	Health anxiety	189.5	50	3.79	low
	Trust	884.1	45	19.65	low
External Factor	Social support	132.78	25	5.31	low
	Subjective norm	921.26	30	30.71	low

3.2.2. Heterogeneity Tests

The homogeneity test results of each variable are shown in Table 3. The heterogeneity tests were significant for the studies with high Q ($p < 0.001$) and I2. Therefore, there is heterogeneity in these factors, including age, income, education, gender, perceived ease of use, perceived risk, perceived benefit, self-efficacy, attitude, Internet experience, health anxiety, trust, social support, and the subjective norm. The method of using a random effect model in meta-analysis to test its moderator effect is applicable to a large sample size of studies (k). Therefore, this study adopted the method of removing outliers to improve the accuracy of meta-analysis.

Table 3. Heterogeneity Test.

Variable		K	N	R	Heterogeneity Test				Tau-Squared			
					Q	Df (Q)	*p*	I^2	τ^2	τ	Se	Var
Demographic Characteristics	Age	8	16,861	−0.19	341.79	7	0.000	94.1	0.024	0.155	0.056	0.003
	Income	6	14,498	0.13	51.01	5	0.000	95.6	0.006	0.077	0.034	0.001
	Education	8	18,084	0.19	158.12	7	0.000	95.6	0.012	0.110	0.041	0.002
	Gender	10	17,612	−0.29	594.06	6	0.000	98.99	0.040	0.200	0.071	0.005
Cognitive Factors	Perceived usefulness	6	1478	0.55	17.18	5	0.004	70.9	0.011	0.105	0.050	0.003
	Perceived ease of use	4	1169	0.37	25.21	3	0.000	88.1	0.027	0.164	0.085	0.007
	Perceived behavioral control	3	986	0.31	15	2	0.001	86.7	0.019	0.138	0.086	0.007
	Perceived risk	6	2347	−0.42	165.07	4	0.000	96.97	0.088	0.297	0.124	0.015
	Perceived benefit	7	5335	0.47	287.91	6	0.000	97.9	0.206	0.454	0.145	0.021
	Perceived cost	4	967	−0.25	5.07	2	0.031	60.5	0.0052	0.072	0.058	0.003
Internal Factors	Self-efficacy	9	2855	0.36	138.73	8	0.000	94.2	0.111	0.333	0.151	0.023
	Attitude	5	1837	0.52	163.00	4	0.000	97.5	0.072	0.268	0.122	0.015
	Internet experience	8	15,791	0.35	2267.14	7	0.000	99.69	0.122	0.349	0.124	0.015
	Health anxiety	8	9083	0.19	105.11	7	0.000	93.3	0.149	0.386	0.055	0.003
	Trust	7	9747	0.37	756.65	6	0.000	99.2	0.072	0.268	0.103	0.011
External Factor	Social support	3	1582	0.39	31.76	2	0.000	93.7	0.054	0.232	0.140	0.020
	Subjective norm	4	1467	0.7	109.93	3	0.000	97.3	0.108	0.329	0.166	0.028

3.3. Meta-Analytic Results

Meta-analysis was used to combine the effect sizes to predict the relationship between and the effects of the influencing factors on OHISB. The revised effect sizes (ES) and confidence interval (CI) are shown as following (Figures 2–5).

3.3.1. Demographic Characteristics Factors

The results from Figure 2 demonstrate that the demographic characteristic factors have medium effect sizes. Gender (r = −0.29, 95%CI = −0.42 to −0.15) is a larger negative influencer than age (r = −0.19; 95% CI = −0.31 to −0.07). Income (r = 0.13; 95% CI = −0.03 to 0.22) and education

(r = 0.19; 95% CI = 0.14 to 0.23) are found to increase the likelihood of OHISB. The effect of education is significantly larger than that of income, which indicates that users with higher education levels are more likely to experience online health information services.

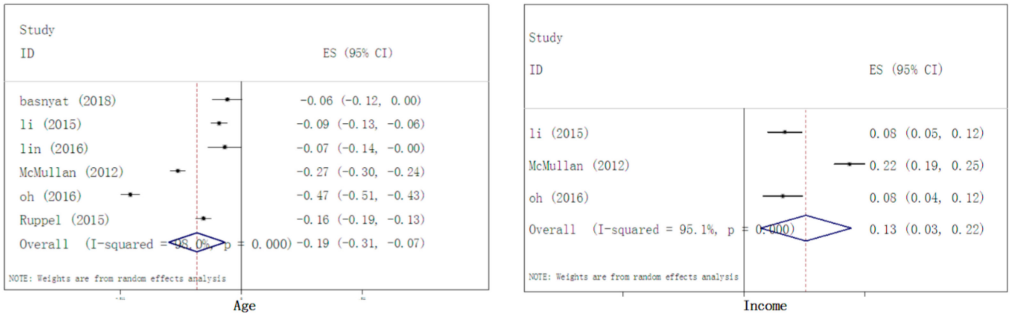


Figure 2. *Cont.*

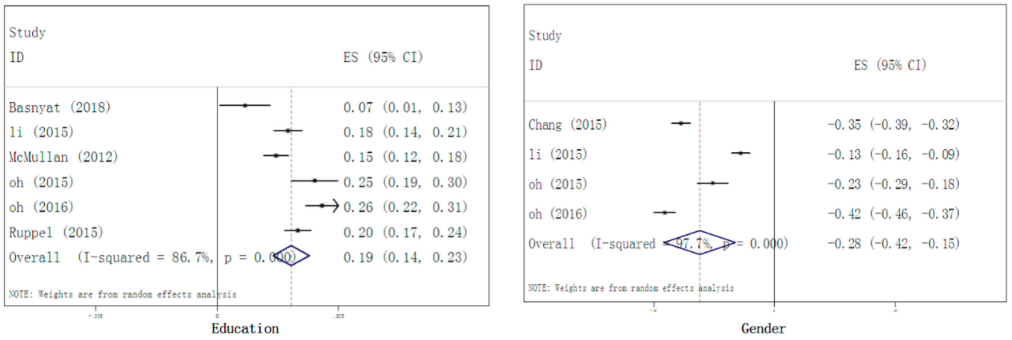


Figure 2. Forest-plot for the effect of demographic factors on OHISB.

3.3.2. Cognitive Factors

The pooled effect size for studies measuring the effect of perceived usefulness on OHISB was r = 0.55 (95% CI = 0.46 to 0.65), indicating that people who subjectively believe that a particular system will better improve the degree of work performance are more likely to conduct OHISB. As shown in Figure 3, perceived benefit (r = 0.47; 95% CI = 0.24 to 0.70), perceived ease of use (r = 0.37; 95% CI = 0.2 to 0.54), and perceived behavioral control (r = 0.31; 95% CI = 0.13 to 0.48) have a strong and significant positive correlation on OHISB. The pooled effect size for perceived risk was r = −0.42 (95% CI = −0.67 to −0.17), which has a significant negative effect on OHISB. Regarding perceived cost, the pooled effect size is negative (r = −0.25; 95% CI = −0.35 to −0.14).

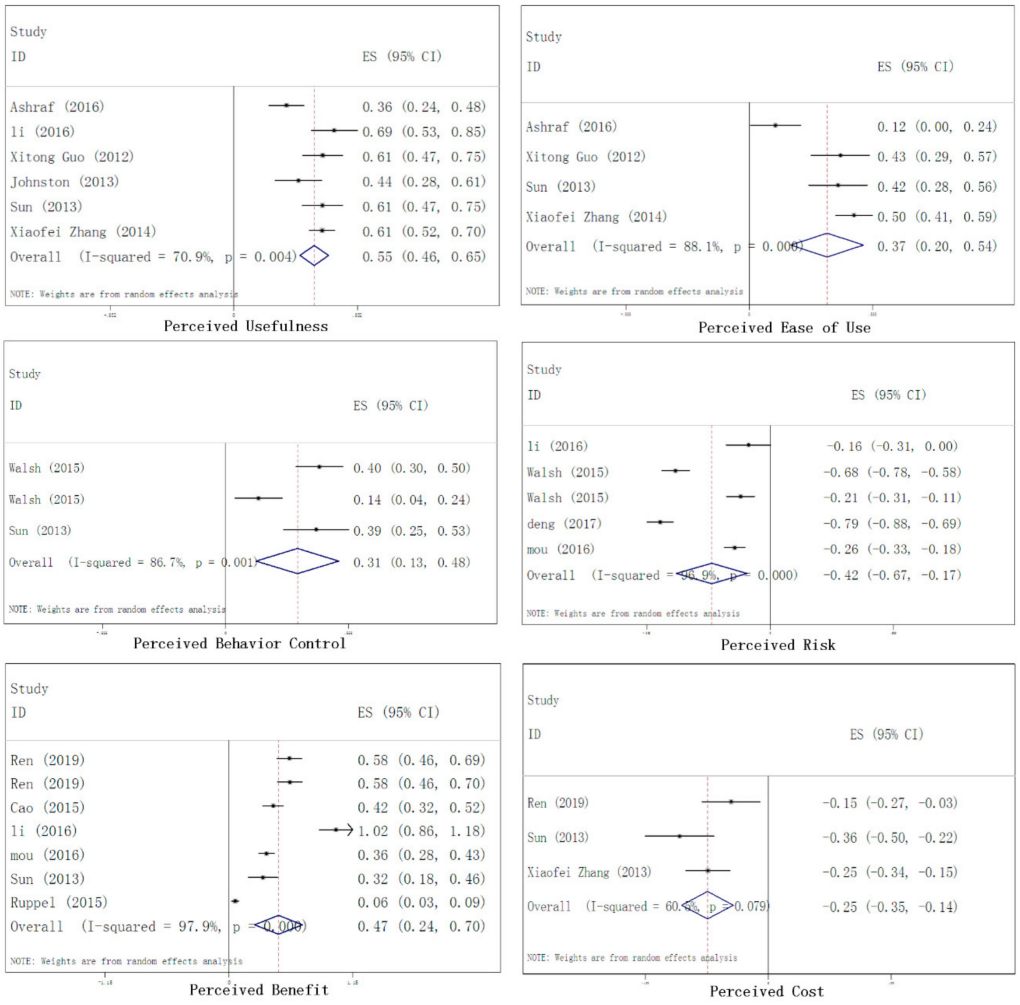


Figure 3. Forest-plot for the effect of cognitive factors on OHISB.

3.3.3. Internal Factors

Attitude represents a large effect value of r = 0.52 with the 95% confidence interval (CI) ranging from 0.22 to 0.81.The effect size of self-efficacy (r = 0.36; 95% CI = 0.23 to 0.50), Internet experience (r = 0.35; 95% CI = 0.03 to 0.66), and trust (r = 0.37; 95% CI = 0.26 to 0.49) have medium correlations with OHISB. The effect size of health anxiety (r = 0.19; 95% CI = 0.14 to 0.25) is only mildly associated with OHISB (see Figure 4).

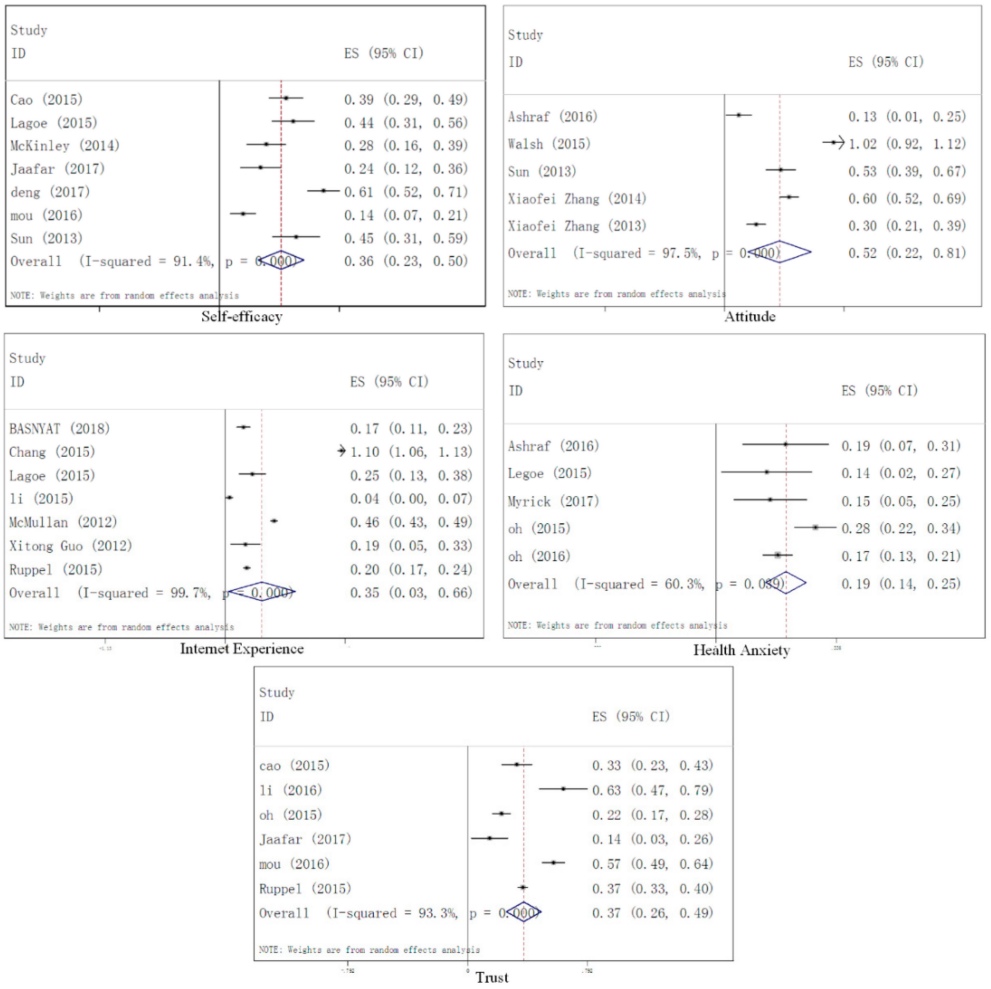


Figure 4. Forest-plot for the effect of internal factors on OHISB.

3.3.4. External Factors

The effect size of the subjective norm (r = 0.7; 95% CI = 0.38 to 1.02) is the largest and most significant, as shown in Figure 5. On the other hand, social support (r = 0.39; 95% CI = 0.15 to 0.63) displays medium correlation to OHISB.

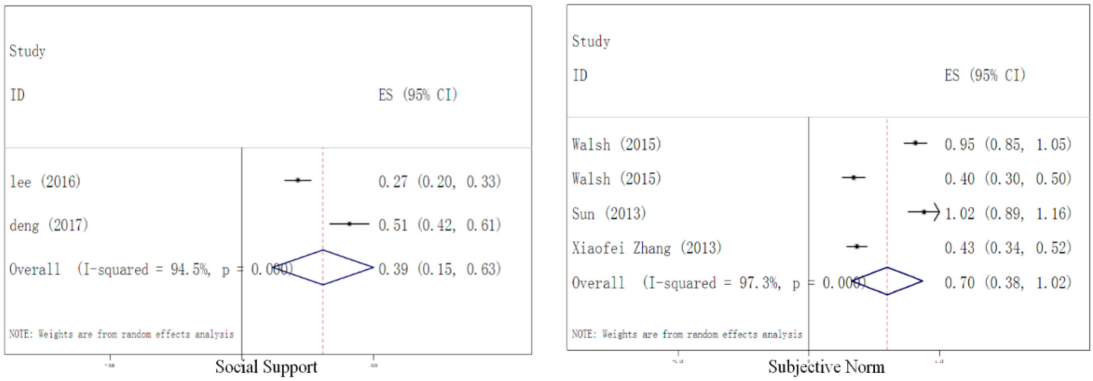


Figure 5. Forest-plot for the effect of external factors on OHISB.

4. Discussion

We reviewed existing research on key factors of OHISB. Seventeen factors related to OHISB were included and analyzed. A meta-analysis was applied to reconcile the contradictory results of the effect of key factors on OHISB.

The results of the meta-analysis indicate that subjective norm has clearly the largest positive impact on users' OHISB. Linking this result with previous literature, a possible explanation is that users tend to make their decisions or perform actions with a new system because they are influenced by people who are important to them [11,30]. As a new auxiliary tool to optimize health service systems and meet users' health information needs, online health websites are neither well known nor trusted by users. Based on the theoretical mechanism of internalization and identification, users' information behavior process goes through the belief-affective-behavior hierarchy. In brief, subjective norms can directly influence individual behavior by enhancing user trust. The results propose that persuasive social information is more trustworthy, which is consistent with previous studies [2].

We should focus on these determinants (e.g., subjective norm, perceived usefulness, and attitude) to improve users' OHISB in the future. Cognitive factors and internal factors in OHISB is measured with multiple dimensions [22]. Our results show that most of the cognitive factors (including perceived usefulness, perceived ease of use, perceived behavioral control, and perceived benefit) and internal factors (including self-efficacy, Internet experience, and trust) have a positive and medium effect. This indicates that perceived usefulness and attitude are the most critical cognitive and internal factors influencing users' OHISB. The previous studies confirm that perceived usefulness and attitude have stronger effects on OHISB [30,31,40], and our meta-analysis results came to the same conclusion. There is a small correlation between all of the demographic characteristics and OHISB. Meanwhile, individuals who are male, younger, more educated, and better paid are more likely to engage in OHISB. The meta-analysis also points out that there is a small correlation between perceived cost and OHISB. The perceived cost can be divided into cognitive costs and execution costs, referring to users' psychological, cognitive responses, or evaluation of online health information seeking and the time, materials, or other resources it takes [11]. Therefore, the conclusion that users' online health information seeking behavior is influenced by time, ability, and other factors is convincing, just as previous studies have suggested [1,11,36].

Previous studies proposed that the effect of high Internet penetration rate and the accessibility of online health information reduce users' cognitive costs [1]. The resources users spend on OHISB for learning and using the technology is less than before. It shows that users' Internet experience is gradually maturing, which is conducive to their health information-seeking behavior. Meanwhile, the meta-analyses indicate that internal factors, health anxiety, for example, also show a small link with online health information seeking behavior compared with other factors. Health anxiety is a fear of illness, typically characterized by common physical symptoms being misinterpreted as signs of serious illness [8]. This finding corresponds with previous research into understanding the psychological mechanisms behind online health information seeking effects [8,11,16]. The explanation is that emotions are transient, and after the fear subsides, the motivation to search for health information online also decreases or disappears [28]. In a word, the results of the meta-analysis provide some guidance to help us better understand what motivates and discourages users from searching for health information online.

5. Conclusions

Our results have great significance in understanding the determinants of OHISB. The 17 influencing factors were identified in the meta-analysis, divided into four dimensions, including demographic characteristic factors, cognitive factors, internal factors, and external factors. The largest effect size was subjective norms, followed by perceived usefulness and attitude. This result shows that users are more likely to take action when OHISB has been performed previously by people who have a significant influence on them. Compared with subjective norms, although there is a weaker correlation between

perceived usefulness and attitude and OHISB, the effectiveness of adopting technology and the positive attitude of users still have an important impact on access to health resources from the Internet. The negative correlation between perceived cost and OHISB is small, suggesting that users are less affected by resource constraints and have more time, money, or cognitive ability to conduct OHISB. As a negative emotion, health anxiety has a small impact on OHISB.

Limitations of the Study and Future Research

Some potential limitations in the meta-analysis are worth improving. First of all, in the meta-analysis, the number of studies on screening samples for each factor was small, the maximum quantity was nine, while the minimum quantity was three. Second, variables in different studies are different, which lead to the failure of meta-analysis on some variables due to the lack of data. Therefore, in the future, we can analyze and explain the relationship between these variables and OHISB in more detail. The third limitation is that this study does not discuss what factors moderate the relationship to OHISB. The fourth, another limitation of our meta-analysis, is that the relationship between other discrete emotions (e.g., hope, interest, inspiration) and OHISB was not discussed. Hence, additional discrete emotions should continue to be investigated in the future. Finally, we did not consider "PsychInfo" And "PubMed" to supplement the missing documents. Therefore, we will value this point in future research.

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