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Determinants and Cross-National Moderators of Wearable Health Tracker Adoption: A Meta-Analysis

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Abstract: Wearable health trackers improve people's health management and thus are beneficial for social sustainability. Many prior studies have contributed to the knowledge on the determinants of wearable health tracker adoption. However, these studies vary remarkably in focal determinants and countries of data collection, leading to a call for a structured and quantitative review on what determinants are generally important, and whether and how their effects on adoption vary across countries. Therefore, this study performed the first meta-analysis on the determinants and cross-national moderators of wearable health tracker adoption. This meta-analysis accumulated 319 correlations between nine determinants and adoption from 59 prior studies in 18 countries/areas. The meta-analytic average effects of the determinants revealed the generalized effect and the relative importance of each determinant. For example, technological characteristics generally had stronger positive correlations with adoption than consumer characteristics, except for privacy risk. Second, drawing on institutional theory, it was observed that cross-national characteristics regarding socioeconomic status, regulative systems, and cultures could moderate the effects of the determinants on adoption. For instance, the growth rate of gross domestic product decreased the effect of innovativeness on adoption, while regulatory quality and control of corruption could increase this effect.

Keywords: meta-analysis; wearable health trackers; wearable healthcare technology; cross-national

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1. Introduction

Wearable health trackers can monitor a user's biophysical and biochemical information and thus can help individuals improve lifestyle-related disorders and personal care [1,2]. In light of this, wearable health trackers provide benefits to a person's quality of life and contribute to the growing public interest in health and the sustainability of the society [2,3]. Especially in tracking and fighting the progression of COVID-19, wearable technology plays a key role [4]. ABI Research [5] expects that over 100 million wearable devices capable of tracking and monitoring will ship to healthcare organizations and patients within the next five years. However, not all wearable health trackers are favorable to consumers [6,7]. Therefore, obtaining insights into the determinants of wearable health tracker adoption is important [8].

Understanding the determinants that influence wearable health tracker adoption has attracted substantial academic attention. More than 80 empirical studies have recently emerged in attempts to identify a broad range of potential determinants of wearable health tracker adoption (e.g., [7,9,10]). These studies differ remarkably in which determinants they focus upon and the countries from which data were collected. For example, some studies emphasize the importance of an individual's interest in health, which drives wearable health tracker adoption (e.g., [11,12]), whereas other studies focus on consumer innovativeness (e.g., [13,14]). Prior studies collected data from across the world, such as in Asia (e.g., [15]), in Europe (e.g., [16]), in North America (e.g., [17]), in South America (e.g., [18]), and in Africa (e.g., [19]).

The significant variances in the determinants focused upon and the countries from which data were collected raise multiple questions about wearable health tracker adoption, including the following: What determinants of wearable health tracker adoption are frequently identified in the literature? Globally, what determinants are the most influential in wearable health tracker adoption? Do the effects of the determinants on adoption change between countries? If so, what cross-national characteristics can explain the varying effects of these determinants? These questions are important since wearable health trackers have a global market and consumers around the world have different consumption beliefs and habits, and thus, practitioners and researchers should know what determinants they need to focus upon in different countries [6,20,21]. To answer these important questions, calls for empirical generalizations on wearable health tracker adoption across countries have been made (e.g., [6,20,21]). This article, therefore, performed the first meta-analysis to provide a structured and quantitative review of the determinants and cross-national moderators of wearable health tracker adoption.

This study is divided into several sections. The authors initially introduce the theoretical background of the determinants and moderators of wearable health tracker adoption. Then, the authors explicate the methodologies. Subsequently, the results are presented. This paper closes with a discussion of theoretical, managerial, and future research implications.

2. Proposed Model

2.1. Definition of Wearable Health Trackers

In line with prior studies (e.g., [8,22,23]), this study defines wearable health trackers as wearables that can be readily worn or attached anywhere on the body (mainly the wrist), which automatically track a user's various types of health information anytime and provide real-time feedback. Representative examples of wearable health trackers are fitness trackers (e.g., Jawbone, Fitbit, and Nike Fuel Band), smartwatches (e.g., Apple Watch and Samsung Galaxy Watch), smart rings (e.g., Oura and Motiv), and smart shoes (e.g., Garmin and Adapt BB). These trackers help users monitor their physical movements, sleeping patterns, heart rates and pulses, breathing, emotions and feelings, blood oxygen levels, glucose levels, and body temperatures based on a variety of sensors [8,24,25].

2.2. Determinants of Wearable Health Tracker Adoption

Shown in Figure 1 is the conceptual framework of this meta-analysis. To define the focal determinants of wearable health tracker adoption, this paper followed the three-step procedure used in prior meta-analyses (e.g., [26–28]). Specifically, first, this paper chose the correlations between determinants and wearable health tracker adoption as the effect sizes because correlations are the most common metric used to describe the relationship between determinants and wearable health tracker adoption. Additionally, correlations were widely accepted in prior meta-analyses as effect sizes (e.g., [26–28]). Second, in reviewing empirical studies that provide the effect sizes of the determinants of wearable health tracker adoption, this paper identified the determinants that have similar definitions but operate under different names, such as ease of use in Kim and Shin (2015) [10] and effort expectancy in Talukder et al. (2020) [14]. Hence, this paper applied a single determinant definition (see Table 1) to code existing research. Third, this paper included a determinant in the meta-analysis only if more than ten studies from at least five countries/areas offered a correlation between that determinant and wearable health tracker adoption. This strategy was recommended by prior meta-analyses (e.g., [26,27]) because requiring a minimum number of studies can ensure high-level empirical generalization [26,27] and requiring a minimum number of countries/areas provides validity for the cross-national moderator analyses [26,27].

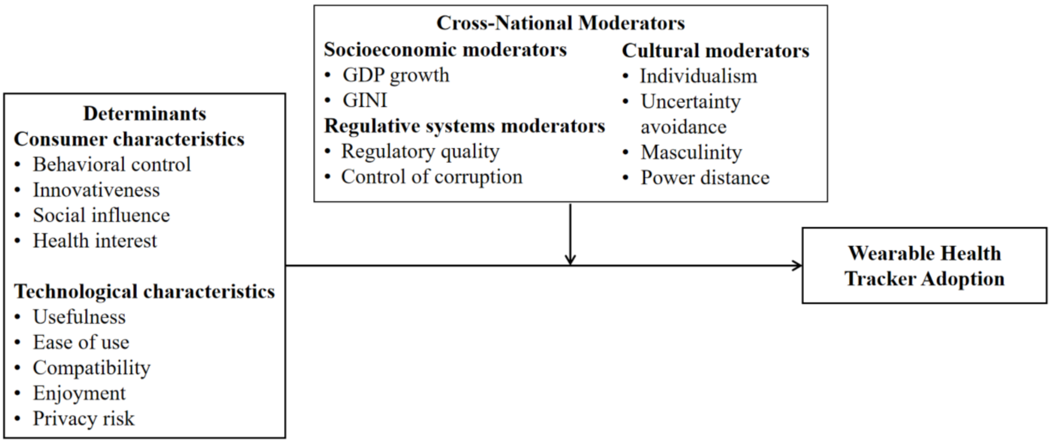

Figure 1. A meta-analytic framework for wearable health tracker adoption.

Table 1. Constructs in the meta-analysis.

Constructs	Definitions	Expected Effect	Common Aliases	Exemplary Papers
Wearable health tracker adoption	Attitude and behavioral intentions towards a wearable health tracker	\	Attitude towards wearable health trackers and adoption/purchase/usage intention	[29,30]
		Consumer characteristics		
Behavioral control	A belief about the presence or absence of requisite knowledge, resources, and opportunities	Positive	Self-efficacy and facilitating conditions	[14,31]
Innovativeness	Underlying predisposition of consumers to try new products	Positive	Resistance to change (reversed coding) and openness	[32,33]
Social influence	Influence from a consumer's social network on adopting a technology	Positive	Subjective norms	[18,34]
Interest in Health	The degree to which a consumer is interested in improving or maintaining health	Positive	Health belief, vulnerability (reversed coding), and severity (reversed coding)	[32,35]
		Technological characteristics		
Usefulness	The degree to which using a technology is beneficial to users' tasks	Positive	Performance expectancy and functionality	[10,36]
Ease of use	The degree to which using a technology is free of effort	Positive	Effort expectancy and convenience	[15,37]
Compatibility	The extent to which a technology is perceived as consistent with one's existing values, past experiences, and lifestyle	Positive	\	[38,39]
Enjoyment	The degree to which using a technology is enjoyable	Positive	Hedonic motivation, affective quality, and emotional value	[40,41]
Privacy risk	The risk of a technology's misusing a consumer's personal information	Negative	Insecurity	[42,43]

Table 1 presents the definition of each determinant, its expected main effect on wearable health tracker adoption, common aliases, and exemplary papers. These exemplary papers have already detailed the theoretical background for the expected main effects, so this work did not explicate the theoretical explanation behind the main effects, especially given that the main goal was to derive global empirical generalizations of these determinants.

The antecedents identified can be broadly categorized as consumer characteristics and technological characteristics. Consumer characteristics capture the personal psychographics of a potential adopter of wearable health trackers. Many studies focus particularly on behavioral control, innovativeness, and social influence. Moreover, since wearable health trackers aim to help users manage their health, prior research argues that the interest of (potential) adopters in health should influence their adoption of wearable health trackers.

The technological characteristics refer to the attributes that consumers use to assess a wearable health tracker. These attributes cover both perceived benefits and perceived costs of using wearable health trackers. Frequently examined benefits include usefulness, ease of use, compatibility, and enjoyment. The adoption of wearable health trackers, as a smart product that can automatically collect personal data, is believed to be influenced by privacy risks.

2.3. Cross-National Moderators of Wearable Health Tracker Adoption

This paper examined how the effects of determinants on wearable health tracker adoption may change across countries through an institutional perspective. An institution is defined as a set of formal regulations and informal restraints that guide political, economic, and social activities in order to maintain order and safety within a society [44]. Building on the definition of institutions, Burgess and Steenkamp (2006) [45] proposed three dimensions to characterize a society: socioeconomic, cultural, and regulative systems. Burgess and Steenkamp (2006) [45] further suggested that it is important to investigate whether empirical findings have strong cross-national generalizability by considering the moderating roles of three institutional dimensions.

Institutions regulate human activities, formulate laws, and encourage beliefs and behaviors that are aligned with shared priorities [46]. Consequently, institutional contexts shape people's consumption beliefs and habits and, in turn, determine the way in which consumers assess firms and their products [45,47]. In light of this, this paper adopted institutional theory to explore whether the characteristics of socioeconomic, cultural, and regulative systems can influence the effects of the determinants of wearable health tracker adoption.

Following prior international studies (e.g., [26]), this paper utilized two main important economic indexes to capture socioeconomic status: GDP growth rate and income inequality measured by GINI coefficients. Furthermore, two important features of national regulative systems are regulatory quality and control of corruption [26], which were introduced into the framework. Regulatory quality refers to "the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development" [26]; control of corruption captures the presence of institutional structures that can prevent bribery and misuse of the power [26].

Finally, this paper applied Hofstede's (2001) [48] cultural framework to measure the differences among cultural systems, which is the most popular structure used to characterize cultural differences. There are four main Hofstede's cultural dimensions: individualism (i.e., the extent to which people are expected to be self-reliant and distant from others), uncertainty avoidance (i.e., societal tolerance of ambiguity or the unknown), masculinity (i.e., societal preference for masculine values, such as competitiveness), and power distance (i.e., the extent to which members of a society accept unequal distributions of power).

The usage of an institutional view yields substantive cross-national characteristics, which allows for a comprehensive analysis on how and whether the relationship between determinants and wearable health tracker adoption varies across countries. Considering such a large number of moderating effects in the framework, this paper did not theorize each effect. Instead, this work empirically examined these moderating effects in an exploratory way.

3. Methodology

3.1. Database Development

Literature search. Drawing on several recent qualitative literature reviews related to wearable health trackers (e.g., [8,20,24,49]), this paper generated a broad set of search items: ("wearable fitness" or "fitness wearable" or "wearable activity" or "activity wearable" or "sports wearable" or "wearable sports" or "fitness tracker" or "activity tracker" or "fitness trackers" or "activity trackers" or "smartwatch" or "smartwatches" or "smart watch" or "smart watches" or "wearable healthcare" or "healthcare wearable") and (acceptance or adoption or purchase). With these search terms, this meta-analysis searched for relevant studies from various pertinent electronic databases, including Web of Science, Academic Search Premier, Business Source Premier, Medline, PsycINFO, and Google Scholar. The search efforts were completed in December 2020. Subsequently, one author and one research assistant independently screened the literature.

Coding of variables. This paper followed a seven-step process to build a database from the relevant papers identified. First, this work classified the determinants and wearable health tracker adoption measures based on the definitions in Table 1. As discussed in Section 2.2, following prior meta-analyses (e.g., [26,27]), this paper selected the correlations as the effect sizes and only focused on determinants with effect sizes presented in over ten studies from at least five countries/areas. Second, this article collected the measure reliabilities of each variable from the papers. Third, this work identified the countries and years from which data were collected in the papers. If some papers did not provide when they collected the data, this study followed prior meta-analyses (e.g., [50]) and used the publication year minus two years. Two years is the average difference between the year of data collection and the publication year across papers. Fourth, using the countries and years from which data were collected, this paper referenced secondary sources (e.g., the World Bank and Hofstede's cultural database) to gather moderator data (see Table 2). Fifth, if there were missing values in the time-varying moderators (e.g., GDP growth), this paper used the data closest to that date. Sixth, if the data in prior studies were collected in multiple countries, this paper accepted the average value of those involved countries. Finally, after the abovementioned steps, if a variable still had missing values, this paper adopted average values.

Table 2. Moderators included in the meta-analysis.

Moderators	Definitions	Data Sources
	Socioeconomic moderators	
GDP growth	The gross domestic product (GDP) growth rate	data.worldbank.org
GINI	The degree of income inequality (0–1)	data.worldbank.org
	Regulative systems moderators	
Regulatory quality	Capability of the government to enact and implement policies and regulations (−2.5, 2.5)	databank.worldbank.org
Control of corruption	The degree of limiting public power for private gains (−2.5, 2.5)	databank.worldbank.org
	Culture moderators	
Individualism	The degree of being self-reliant and distant from others (0–100)	www.hofstede-insight.com
Uncertainty avoidance	The degree of avoiding the unknown and risk (0–100)	www.hofstede-insight.com
Masculinity	The degree of preferring masculine values (0–100)	www.hofstede-insight.com
Power distance	The degree of accepting unequal distributions of power (0–100)	www.hofstede-insight.com

Note: all data accessed on 10 January 2021.

3.2. Meta-Analytical Calculations

Consistent with previous meta-analyses (e.g., [51]), this paper first adjusted the correlations for measurement error by dividing a correlation by the square root of the scale reliabilities of the two variables involved in that correlation. If two corrected correlations were larger than one, they were excluded. Next, this paper transformed the reliability-corrected correlations using Fisher's Z formula: $0.5\ln((1 + r)/(1 - r))$, where r refers to an adjusted correlation. After that, this paper performed the meta-analysis using hierarchical linear modeling [52], which can account for the dependency of multiple effect sizes in the same study. The estimated model is as follows:

$$Z_{ij}^{m} = \alpha_0^{m} + \alpha_k^{m} X_{k,ij}^{m} + \mu_j^{m} + \varepsilon_{ij}^{m} + v_{ij}^{m}, \quad (1)$$

where Z_{ij}^m is the *i*-th Z effect size of *m*-th determinant from study *j*, α_0^m is the intercept, α_k^m is the parameter estimate of the *k*-th cross-national moderator $X_{k,ij}^m$, μ_j^m indicates the between-study error term, ε_{ij}^m represents the between-effect size within-study error term, and v_{ij}^m is the sampling error. This paper estimated this model using the maximum likelihood method because it yields robust, efficient, and consistent estimates [53]. The estimation was operated with the package metafor in R [54].

With the framework of hierarchical linear modeling, this paper conducted two steps for each of the focal determinants separately. First, this paper estimated the intercept α_0^m without introducing moderators into Equation (1). In that case, the estimated α_0^m is exactly the average Z effect size of the *m*-th determinant. This paper then computed the average correlation between the *m*-th determinant and wearable health tracker adoption by transforming this estimated Z coefficient back to a correlation based on Fisher's Z formula. The computed average correlation represents the average effect of the *m*-th determinant. Second, this paper performed simple moderator analyses by adding each cross-national moderator in turn into Equation (1). For example, to estimate the moderating effect of GDP growth rate for the *m*-th determinant, this paper only introduced the GDP growth rate into Equation (1) without any other moderators. This simple moderator analysis was suggested for the case where the number of effect sizes for a determinant was not much larger than the number of moderators of interest [26]. Notably, this paper adopted four cut-off *p*-values (i.e., $^{+}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$) to indicate the different significance levels of the estimates.

4. Results

4.1. Database Description

The database search yielded 566 records (see Figure 2). After removing duplicates, 384 unique records remained. Then, one author and one research assistant independently screened the title and abstract and identified the same 104 relevant papers. Furthermore, the author and the assistant read the full text of each paper and found 50 papers that provided effect sizes for the focal determinants (see Table 3).

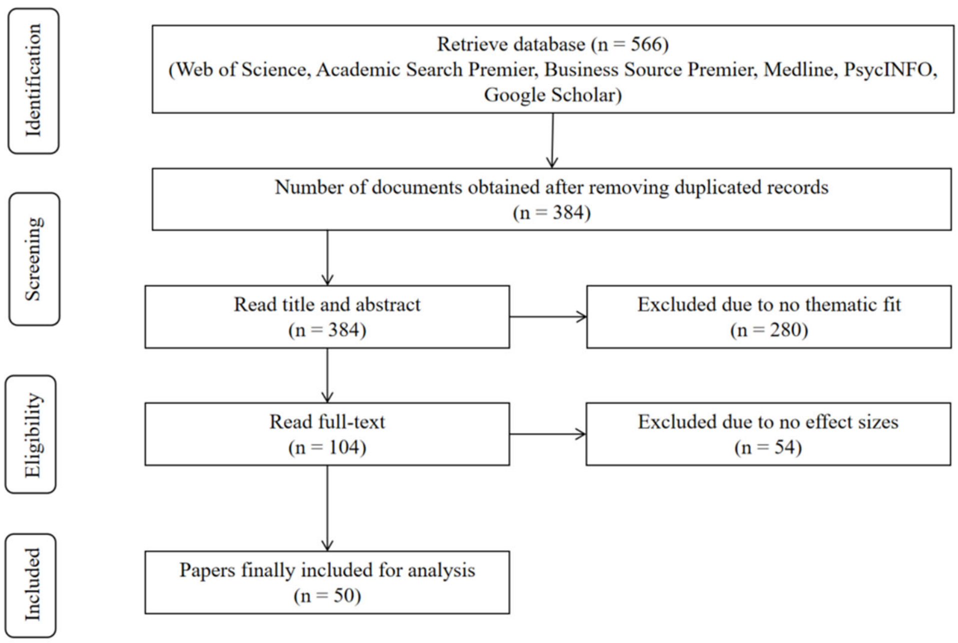

Figure 2. Data collection process.

Table 3. Articles included in the meta-analysis.

Reference Number	Authors	Year	Sample Size	Determinants Included [1]	Countries/Areas
[19]	Adebesin and Mwalugha	2020	232	9	Kenya and South Africa
[32]	Asadi et al.	2019	178	2, 4, 5, 6, 7	Malaysia
[55]	Barbu, Militaru, and Savu	2020	52 (male sample)	2, 3, 5, 6, 7, 8	Romania
[55]	Barbu, Militaru, and Savu	2020	52 (female sample)	2, 3, 5, 6, 7, 8	Romania
[56]	Baudier, Ammi, and Wamba	2020	1197	3, 5, 6, 8	U.S.
[57]	Beh et al.	2021	271	1, 3, 4, 5, 6, 8	Malaysia
[58]	Bölen	2020	348	5	Turkey
[6]	Cheung et al.	2019	171	2, 4, 5, 9	Hong Kong
[59]	Cheung, Leung, and Chan	2020	211	2, 5, 6, 9	Hong Kong
[60]	Choe and Noh	2018	1500	5, 6, 7	South Korea
[13]	Choi and Kim	2016	562	2, 5, 6, 7, 8	South Korea
[41]	Choi, Hwang, and Lee	2017	120	3, 4, 5, 6, 8, 9	U.S.
[61]	Choi, Ko, and Lee	2018	248	5, 8, 9	South Korea
[62]	Chuah et al.	2016	226	5, 6	Malaysia
[40]	Dutot, Bhatiasevi, and Bellallahom	2019	124	5, 6, 8	China
[40]	Dutot, Bhatiasevi, and Bellallahom	2019	206	5, 6, 8	Thailand
[40]	Dutot, Bhatiasevi, and Bellallahom	2019	116	5, 6, 8	France
[12]	Gao, Li, and Luo	2015	232 (fitness information tracker)	1, 3, 4, 5, 6, 8, 9	China
[12]	Gao, Li, and Luo	2015	230 (medical information tracker)	1, 3, 4, 5, 6, 8, 9	China
[63]	Gao, Zhang, and Peng	2016	180	5, 6, 7	China
[38]	Ghazali et al.	2020	155 (sample with high satisfaction)	3, 6, 7	Malaysia
[38]	Ghazali et al.	2020	153 (sample with low satisfaction)	3, 6, 7	Malaysia
[64]	Gupta et al.	2020	684	5	India
[33]	Hsiao	2017	170 (adopters of smartwatches)	2, 6, 7	Taiwan
[33]	Hsiao	2017	170 (non-adopters of smartwatches)	2, 6, 7	Taiwan
[65]	Hsiao and Chen	2018	260	5, 6, 8	Taiwan
[66]	Kao, Nawata, and Huang	2019	226	2, 3, 5, 6	Taiwan
[67]	Kim	2016	200	1, 5, 6, 8	South Korea
[42]	Kim and Chiu	2019	247	2, 5, 6, 9	South Korea
[10]	Kim and Shin	2015	363	5, 6, 8	South Korea
[68]	Kranthi and Ahmed	2018	386	1, 2, 3, 5, 6, 8	India
[69]	Lee	2021	409	3, 5, 6, 8	U.S.
[31]	Lee and Lee	2018	369 (sample aware of fitness trackers)	1, 2, 3, 4	South Korea
[31]	Lee and Lee	2018	247 (sample unaware of fitness trackers)	1, 2, 3, 4	South Korea
[43]	Li et al.	2016	333	2, 5, 9	China
[39]	Li et al.	2019	146	1, 3, 5, 6, 7	China
[34]	Lunney, Cunningham, and Eastin	2016	206	3, 5, 6	U.S.
[70]	Naglis and Bhatiasevi	2019	452	1, 5, 6, 7, 8	Thailand
[71]	Nascimento, Oliveira, and Tam	2018	574	5, 6, 8	U.S.
[72]	Niknejad et al.	2020	100	1, 3, 5, 6, 8, 9	Malaysia
[37]	Ogbanufe and Gerhart	2018	295	5, 6	U.S.
[73]	Pal, Funilkul, and Vanijja	2020	312	3, 5, 8, 9	Thailand
[74]	Papa et al.	2020	273	5, 6, 9	India
[17]	Paré, Leaver, and Bourget	2018	580	5, 6	Canada
[75]	Park, Kim, and Kwon	2016	877	1, 2, 5, 6	South Korea
[16]	Reith et al.	2020	582	3, 5, 6, 9	Germany
[18]	Reyes-Mercado	2018	176 (adopters of fitness wearables)	1, 3, 5, 6	Mexico
[18]	Reyes-Mercado	2018	187 (non-adopters of fitness wearables)	3, 5, 6	Mexico
[76]	Sergueeva, Shaw, and Lee	2020	277	1, 3, 4, 5, 8, 9	U.S.
[36]	Song, Kim, and Cho	2018	236	1, 5	U.S.
[15]	Talukder et al.	2019	392	1, 2, 3, 5, 6, 7, 8	China
[14]	Talukder et al.	2020	325	1, 2, 3, 5, 6, 8	China
[77]	Tsai et al.	2020	81	2, 5, 6	Taiwan
[29]	Wang and Hsu	2019	432	5, 8	China
[78]	Wang et al.	2020	406	1, 3, 5, 6	China
[79]	Wu et al.	2020	254	8	China
[30]	Wu, Wu, and Chang	2016	212	3, 6, 7, 8	Taiwan
[35]	Zhang et al.	2017	197 (male sample)	2, 4, 5, 6, 9	China
[35]	Zhang et al.	2017	239 (female sample)	2, 4, 5, 6, 9	China

Note: [1] determinants included in the study: 1. behavioral control; 2. innovativeness; 3. social influence; 4. interest in health; 5. usefulness; 6. ease of use; 7. compatibility; 8. enjoyment; and 9. privacy risk.

The database contains 321 effect sizes from nine determinants for wearable health tracker adoption. The effect sizes were collected from 59 studies/samples in 50 papers, with a total sample size of 18,589. Prior studies were conducted in 18 countries/areas, covering Asia (Mainland China, Hong Kong, Taiwan, India, South Korea, Malaysia, Thailand, Turkey, and Singapore), Europe (Germany, Romania, France, and the U.K.), North America (Canada, the U.S., and Mexico), and Africa (Kenya and South Africa).

4.2. Analysis of the Determinants

Shown in Table 4 is an overview of the average correlations for all of the considered determinants of wearable health tracker adoption from the meta-analysis. As indicated by the significance levels of the Q statistic test of homogeneity [27,80], all of the relationships were heterogeneous across studies, justifying the need for empirical generalizations and calling for moderator analyses. Furthermore, the fail-safe sample sizes were much larger than the number of samples, which suggests that there exists no serious publication bias in the database [27,80].

Table 4. Mean effect sizes of the determinants of wearable health tracker adoption.

Determinants	Number of Countries/ Areas	Number of Studies	Number of Effect Sizes	Total Sample Size	Average r_a	95% Confidence Interval	Q-Value	Fail-Safe N
				Consumer characteristics				
Behavioral control	7	17	23	5322	0.516 ***	(0.357, 0.646)	1310.317 ***	19,914
Innovativeness	7	20	27	5435	0.482 ***	(0.297, 0.632)	1349.849 ***	14,895
Social influence	13	26	33	7420	0.509 ***	(0.410, 0.596)	891.873 ***	27,930
Interest in health	5	11	14	2531	0.378 ***	(0.250, 0.492)	153.884 ***	2147
				Technological characteristics				
Usefulness	16	50	78	16,627	0.705 ***	(0.655, 0.750)	2584.177 ***	392,536
Ease of use	14	46	65	14,446	0.584 ***	(0.515, 0.646)	1879.088 ***	154,417
Compatibility	6	14	21	4374	0.740 ***	(0.677, 0.792)	303.712 ***	35,266
Enjoyment	12	27	37	8358	0.694 ***	(0.613, 0.760)	974.685 ***	93,525
Privacy risk	11	16	21	4004	−0.410 ***	(−0.586, −0.197)	930.575 ***	6170

Note: *** $p < 0.001$.

All determinants showed significant positive correlations, except for the negative correlation for privacy risk. The technological characteristics (except for privacy risk) were generally more strongly associated with wearable health tracker adoption than the consumer characteristics.

The effects for each category are summarized as follows. Among the technological variables, the most important determinant was compatibility ($r_a = 0.740$, $p < 0.001$) rather than usefulness ($r_a = 0.705$, $p < 0.001$) and ease of use ($r_a = 0.584$, $p < 0.001$), although the latter two also had strong correlations with wearable health tracker adoption. This finding indicates that a new wearable health tracker should be not too innovative and not too inconsistent with consumers' habits and lifestyles. Furthermore, it was observed that enjoyment also positively increases wearable health tracker adoption ($r_a = 0.694$, $p < 0.001$), revealing that wearable health trackers are not totally utilitarian products to consumers. Consumers usually also have hedonic consumption goals towards using wearable health trackers. Finally, privacy risk was found to negatively correlate with wearable health tracker adoption ($r_a = -0.410$, $p < 0.001$). This observation is understandable since wearable health trackers can automatically collect personal health information and thus consumers are worried about privacy breaches.

For the consumer characteristics, behavioral control had the highest correlation with wearable health tracker adoption ($r_a = 0.516$, $p < 0.001$). In other words, consumers with requisite knowledge and resources are more willing to accept wearable health trackers. Similar to behavioral control, social influence also showed a strong positive correlation with wearable health tracker adoption ($r_a = 0.509$, $p < 0.001$), revealing that consumers' social networks influence their adoption. Additionally, innovative consumers have a stronger willingness to accept wearable health trackers ($r_a = 0.482$, $p < 0.001$). Finally, consumers also adopt wearable health trackers if they pay more attention to their health ($r_a = 0.378$, $p < 0.001$).

4.3. Analysis of the Moderators

Table 5 presents summary statistics of the moderators for each determinant. Based on hierarchical linear modeling, this paper investigated the moderating effects of cross-national characteristics (see Table 6). The model revealed that the effects of usefulness, compatibility, and privacy risk on wearable health tracker adoption do not change across countries, while the effects of the remainder are moderated by cross-national characteristics.

Socioeconomic moderators. Socioeconomic status matters, but only GDP growth can serve as a moderator for wearable health tracker adoption, while GINI cannot moderate any determinant. In particular, GDP growth rate negatively influenced the effect of innovativeness on wearable health tracker adoption ($\beta = -0.094$, $p < 0.05$). This finding is reasonable since countries with high GDP growth rates generally refer to developing economies with higher-than-normal poverty and most consumers own few assets and are highly price-sensitive [26]. Therefore, consumers are less attracted to positive drivers of wearable health tracker adoption due to financial limits, in line with a recent finding [10] that the cost of wearable health trackers negatively influences consumer intention to adopt.

Regulative systems moderators. The characteristics of both regulatory systems can enhance the positive effects of determinants on wearable health tracker adoption. Specifically, regulatory quality and control of corruption positively influenced the effect of innovativeness ($\beta = 0.303$, $p < 0.05$; $\beta = 0.357$, $p < 0.05$). Moreover, regulatory quality also increased the effect of an interest in health ($\beta = 0.150$, $p < 0.05$). The positive moderating effects of regulative systems are maybe due to the fact that a good regulative system can enhance consumers' trust in a business and can reduce their perceived risk [26,31]. Consumer trust can positively influence their attitude towards products [81,82]. Therefore, consumers are more willing to try wearable health trackers, and thus, positive determinants of wearable health tracker adoption would be more influential.

Cultural moderators. Cultural characteristics can also explain the heterogeneity in the effects of the determinants of wearable health tracker adoption to some degree. It was observed that behavioral control has a stronger effect on wearable health tracker adoption if consumers are in an individualistic culture than a collective culture ($\beta = 0.009$, $p < 0.01$). This is possible because people in an individualistic culture tend to be self-reliant [32] and thus believe more in their capability and resources to make the best use of technologies [83].

Moreover, uncertainty avoidance negatively influenced the effect of social influence on wearable health tracker adoption ($\beta = -0.007$, $p < 0.05$), maybe because people in a society with high levels of uncertainty avoidance dislike risk [32] and are less willing to accept innovations (e.g., wearable health trackers) [84]. Interestingly, uncertainty avoidance increased the effect of enjoyment on wearable health tracker adoption ($\beta = 0.006$, $p < 0.05$). In other words, the hedonic aspects (i.e., enjoyment) of wearable health trackers become more important to consumers with high uncertainty avoidance than ones with low uncertainty avoidance. A prior meta-analysis on sharing economy by Kozlenkova et al. (2021) [26] also identified a positive moderating effect of uncertainty avoidance on hedonic values. These consistent findings suggested that consumers with high levels of uncertainty avoidance are more likely to accept innovations for fun and enjoyment. This is possible because consumers from cultures with high levels of uncertainty avoidance lack a sense of safety [85] and want to use the hedonic benefits (e.g., enjoyment) of wearable health trackers to offset the unhappiness from their safety concerns.

Masculinity had no moderating effects on any determinant of wearable health tracker adoption. In contrast, power distance positively influenced the effect of ease of use on wearable health tracker adoption ($\beta = 0.004$, $p < 0.1$). This is possible because individuals from a culture with high levels of power distance are more willing to accept innovations [86] and thus are more willing to pay attention to the benefits of wearable health trackers.

Table 5. Summary statistics of the moderators.

Moderators	Behavioral Control		Innovativeness		Social Influence		Interest in Health		Usefulness		Ease of Use		Compatibility		Enjoyment		Privacy Risk	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Socioeconomic moderators																		
GDP growth	4.401	2.202	5.015	2.142	4.828	1.954	5.219	2.285	4.521	2.082	4.789	2.059	5.248	1.509	4.644	1.957	4.499	2.455
GINI	0.378	0.043	0.364	0.031	0.387	0.034	0.388	0.032	0.375	0.036	0.376	0.037	0.376	0.03	0.368	0.034	0.383	0.051
Regulative systems moderators																		
Regulatory quality	0.623	0.724	0.832	0.711	0.610	0.657	0.562	0.866	0.749	0.697	0.744	0.667	0.628	0.541	0.676	0.647	0.580	0.892
Control of corruption	0.309	0.682	0.427	0.609	0.290	0.692	0.273	0.715	0.428	0.708	0.419	0.677	0.197	0.427	0.346	0.633	0.326	0.807
Culture moderators																		
Individualism	38.304	29.590	21.815	6.995	37.258	24.642	31.500	25.376	35.532	25.765	31.900	23.046	22.476	4.996	33.824	25.440	33.825	22.817
Uncertainty avoidance	52.957	22.804	63.778	24.459	53.593	22.230	41.357	19.345	58.623	22.879	57.400	22.349	59.762	24.793	60.366	23.257	48.046	21.065
Masculinity	54.565	12.045	48.370	10.039	54.635	9.935	57.500	10.105	51.679	10.948	51.281	10.838	48.238	9.833	49.918	11.577	55.646	10.205
Power distance	66.913	18.508	70.333	13.533	74.029	20.617	74.857	19.560	68.397	17.981	70.238	18.254	78.857	16.977	68.593	16.549	68.681	15.869

Notes: GDP = gross domestic product; SD = standard deviation.

Table 6. Moderating effects of wearable health tracker adoption.

Moderators	Behavioral Control	Innovativeness	Social Influence	Interest in Health	Usefulness	Ease of Use	Compatibility	Enjoyment	Privacy Risk
Socioeconomic moderators									
GDP growth	−0.033 (0.493)	−0.094 * (0.037)	0.013 (0.692)	−0.041 (0.177)	−0.023 (0.305)	−0.008 (0.732)	−0.028 (0.514)	−0.023 (0.515)	0.047 (0.307)
GINI	3.369 (0.141)	1.701 (0.641)	0.349 (0.844)	0.135 (0.950)	1.102 (0.391)	1.659 (0.221)	−2.524 (0.218)	−0.530 (0.808)	−0.044 (0.987)
Regulative systems moderators									
Regulatory quality	0.110 (0.452)	0.303 * (0.020)	0.075 (0.431)	0.151 * (0.027)	0.029 (0.653)	−0.032 (0.661)	−0.115 (0.315)	0.104 (0.321)	−0.040 (0.758)
Control of corruption	0.189 (0.241)	0.357 * (0.026)	0.126 (0.134)	0.141 (0.118)	−0.017 (0.790)	−0.055 (0.429)	−0.144 (0.318)	0.036 (0.745)	−0.055 (0.700)
Culture moderators									
Individualism	0.009 ** (0.008)	0.007 (0.650)	0.002 (0.435)	0.001 (0.734)	−0.001 (0.567)	0.000 (0.976)	0.006 (0.683)	0.000 (0.983)	0.006 (0.173)
Uncertainty avoidance	−0.004 (0.402)	−0.003 (0.437)	−0.007 * (0.012)	0.001 (0.776)	0.000 (0.895)	−0.002 (0.373)	0.000 (0.913)	0.006 * (0.039)	0.006 (0.325)
Masculinity	0.009 (0.285)	−0.002 (0.841)	0.006 (0.313)	−0.009 (0.198)	0.000 (0.984)	0.000 (0.962)	0.005 (0.432)	−0.008 (0.217)	−0.002 (0.908)
Power distance	−0.009 (0.119)	0.004 (0.666)	−0.002 (0.514)	0.000 (0.928)	0.003 (0.199)	0.004 $^{+}$ (0.090)	0.002 (0.664)	0.002 (0.617)	−0.005 (0.477)

Notes: $^{+}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; GDP = gross domestic product; beta (p value) in cells.

5. Discussion

Undertaking a meta-analytic review of prior research, this study investigated the determinants that influence wearable health tracker adoption and their cross-national moderators. This paper identified nine important determinants after integrating 59 studies with a total sample size of 18,589 from 18 countries/areas. This database allowed the derivation of the global generalized effects of determinants. This paper further drew on institutional theory to investigate how cross-national characteristics moderate the effects of these determinants. The results make important academic contributions and yield managerial insights.

5.1. Theoretical Contributions

Recent studies have called for research to empirically generalize findings on wearable health tracker adoption across countries (e.g., [6,20,21]). To answer their calls, this paper performed the first meta-analysis on the determinants and cross-national moderators of wearable health tracker adoption. This meta-analysis makes two main contributions to the literature. First, as Table 3 shows, prior studies often focus on the part of the important determinants. This meta-analysis yielded a comprehensive overview of important determinants covering consumer characteristics and technological characteristics. This overview offers an opportunity to systematically compare the relative importance of all important determinants. The global generalization revealed that the technological characteristics generally have stronger correlations with wearable health tracker adoption than the consumer characteristics, except for privacy risk. Among the consumer characteristics, behavioral control had the strongest correlation with adoption. Interest in health is relatively less frequently examined in the literature but can significantly increase the willingness to adopt wearable health trackers. For the technological characteristics, compatibility can enhance wearable health tracker adoption to the highest degree. By contrast, privacy risk was negatively correlated with wearable health tracker adoption.

Second, although prior studies have realized that the effects of the determinants of wearable health tracker adoption could change across countries (e.g., [19,87]), these studies often are limited to collecting data within one country and do not focus on cross-national characteristics. Instead, drawing on institutional theory and integrating data from studies conducted in various countries, the paper is the first to explore how three groups of cross-national characteristics moderate the determinants of wearable health tracker adoption. The results showed that all of the determinants are moderated by cross-national characteristics, except for usefulness, compatibility, and privacy risk. As a socioeconomic characteristic, GDP growth negatively influenced the effect of innovativeness on wearable health tracker adoption. On the contrary, the effect of innovativeness can be positively influenced by regulatory quality and control of corruption, two regulatory system characteristics. Furthermore, regulatory quality increased the effect of an interest in health. Cultural characteristics can serve as important moderators. In particular, individualism increased the effect of behavioral control, uncertainty avoidance decreased the effect of social influence but increased the effect of enjoyment, and power distance enhanced the effect of ease of use.

5.2. Managerial Implications

This study provides two main managerial implications. First, the integrated framework and the generalization analysis herein offer firms an overview of what determinants are important for wearable health tracker adoption. Based on the analysis of relative importance, managers can assign resources more effectively by comparing the generalized importance of the determinants. For example, if improvements in usefulness and ease of use require the same amount of monetary investment, a manager should invest in usefulness because the effect of perceived usefulness plays a more important role in consumers' adoption of wearable health trackers than ease of use. Furthermore, unlike other technologies, wearable health trackers aim to help users manage their health by collecting personal information. Naturally, firms need to target consumers that care about their health. Meanwhile, firms should protect consumers' privacy. Otherwise, consumers will have a lower willingness to accept wearable health trackers.

Second, the moderator analyses revealed that firms need to adopt different strategies to develop or promote wearable health trackers around the world. In particular, on the one hand, firms could benefit more by focusing on appropriate consumers in different countries. For example, firms can achieve better market performance if they target consumers that are innovative in a country with a low GDP growth rate or with a good regulatory system. In an individualistic culture, firms can sell more wearable health trackers to consumers that own strong behavioral control. On the other hand, firms should invest in or promote different technological attributes across countries. For instance, firms can achieve higher market success if they emphasize the enjoyment of using wearable health trackers in a culture with high levels of uncertainty avoidance. Finally, firms can always make investments in the usefulness, compatibility, and enjoyment of wearable health trackers, since these three determinants always have strong, positive correlations with wearable health tracker adoption across countries.

5.3. Limitations and Future Research

The current work has some limitations and provides avenues for future research. First, to ensure high levels of global generalization, this paper only focused on the most common determinants in the literature. Therefore, some understudied but potentially important determinants (e.g., cost of wearable health trackers in [10]) definitely deserve further research. When more empirical studies on wearable health tracker adoption appear, researchers can update the current meta-analysis by adding more important determinants. Second, the overview of determinants of wearable health tracker adoption shows the frequency of each determinant in extant empiricism, indicating which factor demands additional research. For example, per the frequency counts, interest in health has not received sufficient attention, although the analysis in this paper showed a positive effect of interest in health on adoption. Third, the generalization reveals that to build a more comprehensive framework for explaining wearable health tracker adoption, further research needs to include all of the determinants identified in the framework. In addition, with these generalized effects, researchers can discern whether their conclusions are reliable by comparing their estimated effects with the generalized results in this paper. Fourth, the existence of cross-national moderating effects indicates that future work should investigate whether their conclusions are contingent on cross-national characteristics.

6. Conclusions

This study sought to advance research on the characteristics that explain consumers' adoption of wearable health trackers through a meta-analytic review of prior studies. This meta-analysis identified important determinants of wearable health tracker adoption and explained cross-national differences in the effects of determinants on the adoption of wearable health trackers, drawing on the institutional theory. In achieving these outcomes, this paper enhances the understanding of the emerging market of wearable health trackers. The authors encourage researchers to consider the important determinants identified when explaining wearable health tracker adoption and to pay attention to the robustness of their findings to different countries. The authors encourage managers to reassign their resources in terms of the relative importance of determinants and to rethink their global strategies in light of the cross-national moderators.

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