# Determinants of the adoption of wearable devices for health and fitness: A meta-analytical study

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**Abstract:**

Smart wearable technology devices have enabled digital tracking and management of health and fitness parameters. To explore the antecedents and consequences of the adoption of wearable devices, we did a series of meta-analysis using the theoretical frameworks of the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the integrated conceptual model. Fifty-six studies identified from fifty-two articles were short-listed for this meta-analysis. Results from the combined effect size analysis confirmed all the TAM and UTAUT relationships. Along with constructs from traditional technology acceptance theories, other constructs such as innovativeness, compatibility, self-efficacy, and social influence had a significant impact on the behavioral intention to use wearable devices. This study also demonstrates the similarities in the effect sizes for constructs with similar meanings derived in the literature. The combined effects of TAM and UTAUT constructs were compared while examining the adoption of wearable devices. Many of the relationships analyzed in this research were moderated by culture and user type. Implications for research and practice have been discussed.

**Keywords**: Wearable devices, Technology adoption, Healthcare, TAM, UTAUT, and Meta-analysis.

# 1 Introduction

Wearable devices have become very popular due to rapid advancements in information and communication technologies powered by miniaturized sensors. Wearable device shipment volumes grew from 78 million units in 2015 to 444.7 million units in 2020, at an annual growth rate of 22.8% (IDC, 2021). As per market research, spending on wearable devices is expected to reach $82 billion in 2021 (Gartner, 2021). Wearable devices can be broadly classified into five categories: wrist-worn (smartwatches and wristband), head-mounted (smart eyewear and earbuds), e-textiles (smart garments), e-patches, and smart jewelry (Seneviratne et al., 2017). Wearable devices can continuously sense, collect, analyze, and distribute physiological data that helps people to maintain a healthy lifestyle. The 2016 Price Waterhouse Coopers (PwC) survey identified health as a primary reason people choose to use wearable devices (PwC, 2016). Wearable devices have shifted the focus of the healthcare sector from reactive to proactive prevention-oriented interventions that allow the users to take greater responsibility and better control over their health.

Wearable devices are promising tools that enable people to improve their health and fitness. Regular usage of wearable devices leads to continuous monitoring of certain health parameters and thus have the scope to improve the health conditions of people diagnosed with chronic diseases (Gao, Li, & Luo, 2015). Despite the potential benefits, wearable technology devices are currently in the early stage of adoption and commercialization (Asadi, Abdullah, Safaei, & Nazir, 2019; Zhang, Luo, Nie, & Zhang, 2017) and have been facing many challenges. Hence, scholars are trying to identify and understand factors that influence the adoption of wearable technology devices, and derive implications based on them for increased usage.

Many empirical studies have used traditional technology acceptance theories (i.e., technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), etc.) to explore the antecedents and consequences of the adoption of wearable technology devices. Despite a growing body of literature on the adoption of wearable devices, there is no clear consensus on the factors, or the effect sizes of the constructs studied. The studies conducted between different samples, using multiple theories, with varying objectives and from diverse fields, resulted in inconsistent findings. In this study, we investigate four important research gaps found in the literature.

First, TAM is the most widely used framework to investigate the adoption and diffusion of wearable devices (Papa, Mital, Pisano, & Del Giudice, 2020; Paré, Leaver, & Bourget, 2018; Kim & Shin, 2015). TAM explains significant variances in the behavioral intention to use wearable devices. For example, Kim & Chiu, (2019); and Park, Kim, & Kwon (2016) revealed that TAM alone could explain 56.7% and 66.9% variances (respectively) in the intention to use wearable technologies. Despite the explanatory power and wider deployment, tensions exist between TAM relationships. Inconsistent results were reported for the relationship between perceived ease of use and perceived usefulness. While some scholars found perceived ease of use as a significant predictor of perceived usefulness (Papa et al., 2020; Park et al., 2016), others obtained non-significant results (Vongurai, 2020; Chang, Lee, & Ji, 2016). Moreover, the integrative view and cumulative impact of TAM constructs in the adoption of wearable devices is lacking. Thus, the present study employed meta-analysis to quantitatively synthesize TAM relationships and has attempted to clarify the relationships where the conclusions are mixed.

Second, next to TAM, UTAUT is the broadly used theoretical foundation to explore the adoption of wearable devices (Beh, Ganesan, Iranmanesh, & Foroughi, 2021; Talukder, Sorwar, Bao, Ahmed, & Palash, 2020; Sergueeva & Shaw, 2017). Reyes-Mercado (2018) found that UTAUT constructs explain 63.3% of the variances in the behavioral intention to use fitness wearables. However, prior literature indicated a dichotomy among the UTAUT relationships; the same relationships were found to be both significant and non-significant. For instance, while some studies ((Talukder, Chiong, Bao, & Hayat Malik, 2019; Sergueeva & Shaw, 2017) established significant relationship between social influence and behavior intention, others (Beh et al., 2021; Rubin & Ophoff, 2018) reported non-significant results. There is also disagreement on the relationship between facilitating condition and behavioral intention. Owing to these inconsistencies, it is difficult to generalize on factors contributing to the adoption of wearable technologies. Further, the impact of UTAUT relationships vary across studies, and there was no attempt to find a combined effect across the studies. Hence, the present study employs meta-analysis to synthesize the empirical findings across the studies and reconcile inconsistent results to understand the clear impact of the UTAUT framework in the adoption of wearable devices.

Third, studies that investigated the adoption of wearable devices used TAM or UTAUT as base models and extended them using the contextual and external variables for a holistic perspective. Contextual and external variables such as innovativeness and compatibility from diffusion of innovation (DOI), self-efficacy from self-efficacy theory, perceived privacy risk from privacy calculus theory (PCT), and price value were the commonly used constructs to extend TAM or UTAUT. According to Kim and Shin (2015), the integrated model developed by extending TAM with external variables captured 80% of the variance in behavioral intention. Similarly, an integrated research model developed by integrating UTAUT with DOI (Talukder et al., 2019) explained 94% of the variance. Scholars have developed integrated research models by hand picking the constructs that can suit the wearable device's context. A comprehensive research model that can explain the adoption of wearable devices is currently lacking in the literature. Prior studies (Talukder et al., 2019; Park et al., 2016) advocated the need to develop an integrated conceptual model that will reflect the behavior intention of wearers of such devices. To fill this gap, we developed an integrated conceptual framework by taking constructs from the TAM and UTAUT frameworks and extending it with the contextual variables derived from the literature. Further, we conducted meta-analysis to establish the validity of the integrated research model.

Fourth, even though IS literature has established the role of culture in influencing the development, adoption, and usage of technologies (Vance, Elie-Dit-Cosaque, & Straub, 2008), the impact of culture on the adoption of wearable devices is not very clear. Different cultures possess differing levels of availability and access to technologies. Cultural norms influence the attitude and behavior to perform a specific action (Li, Chau, & Van Slyke, 2010). Research has consistently found that the behavior of individuals from eastern and western cultures differ significantly. Published meta-analysis studies have validated the difference between eastern and western cultures in technology adoption (Mehta, Chauhan, Gupta, & Jaiswal, 2021; Zhang, Zhu, & Liu, 2012). Several studies have also investigated wearable devices adoption from a particular country perspective (Macdonald, Perrin, & Kingsley, 2020; Cheung, Leung, & Chan, 2020). Prior studies have established the moderating role of culture while investigating technology acceptance (Mehta et al., 2021; Srite & Karahanna, 2006) and indicated that culture could play a crucial role in determining the success and failure of wearable technologies, and have advocated further research of this angle. Research on the adoption of wearable devices has been applied to different user types (i.e., users and non-users). Reyes-Mercado (2018) investigated the adoption of fitness wearables and found that non-users exhibit differentiated behavior as compared to the users. However, it is unclear how the effect sizes would differ between users and non-users in the wearable technology context. Previous meta-analysis studies have established that user type could significantly moderate the relationships between the antecedents of behavior intention (Tao et al., 2020; King & He, 2006). Convergence and divergence of moderating effect of user types could influence the positioning strategy of wearable devices. To address these gaps, we investigated the moderating role of culture (Eastern vs. Western) and user type (Users vs. Non-users) in the adoption of wearable devices.

In sum, this study employed a meta-analytic approach to better understand the reasons why people use wearable devices to track their health and fitness activities. The study objectives included:

1) Conducting a meta-analysis with TAM and UTAUT frameworks to estimate the magnitude of relationships between the antecedents of behavioral intention to use wearable devices,
2) Developing and validating the integrated conceptual model for the adoption of wearable devices using meta-analysis, and
3) Conducting a moderator analysis underneath the moderating impact of culture and user type.

The series of meta-analysis performed in this study add to the IS adoption literature in general and wearable technology literature in particular. First, quantitative synthesis from prior studies has established the robustness of TAM and UTAUT constructs in the wearable technology context. Based on the empirical evidence, the combined effect sizes of TAM and UTAUT relationships were compared. Second, in accordance with the prior literature, we developed the integrated conceptual model with relevant factors that could influence the adoption of wearable devices. The validity of the integrated model was established using meta-analysis. The integrated model provided a comprehensive understanding of the adoption of wearable devices. Finally, this study reveals the moderating effects of culture and user type. Moderator analysis informs the practitioners on how the differences in culture and user type could influence the adoption and diffusion of wearable technologies.

The remainder of the article is organized as follows. Section 2 reviews the literature on wearable devices and presents the theoretical background with hypotheses; Section 3 describes the research methodology;

Section 4 presents the results; Section 5 discusses the results of the meta-analysis and presents the implications for further research and practice, and Section 6 provides concluding remarks.

# 2 Background

## 2.1 Wearable devices for health and fitness

Wearable devices are accessories or e-garments that can be easily worn on the body parts; these are mini electronic devices embedded with a range of sensors and advanced computational capabilities, providing insightful information to the users (Sergueeva, Shaw, & Lee, 2020). Wearable devices can continuously sense and capture physiological signals triggered by the human body. They can also perform advanced analytics and provide useful information and actionable items to maintain a healthy lifestyle. Even though wearable devices are gaining more attention in the healthcare setting, health and fitness remain the primary application of wearable technology (Beh et al., 2021). Different types of wearable devices used to monitor health and fitness include smartwatches, fitness bands, fitness trackers, smart shoe insole, wearable biometric tracking devices, and smart garments. Among the different types of wearable devices, smartwatches and fitness bands emerged as the most common and widely diffused products in the market (Seneviratne et al., 2017). With advanced computational, storage, and monitoring capabilities, smartwatches emerged as technically superior wearable devices (Kim & Ho, 2021).

Although wearable devices are experiencing rapid technological advancements and gaining market traction in recent times, wearable technology has been in existence for more than two decades. In 2000, IBM launched the first wearable wrist computer with the Linux operating system (Choi & Kim, 2016). The introduction of operating systems in wearable devices opened up several avenues by expanding their scope. Early versions of wearable devices had basic applications such as address books, calculators, and world clock. Garmin pioneered the wearable devices for health and fitness (Webber & Porter, 2009). Garmin 101, launched in 2003, was the first smartwatch with health and fitness functionality, and was equipped with a GPS sensor which enabled the users to track distance, speed and calories burned (Longland, Barfoot, & Harris, 2018).

Ever since the introduction of the first set of devices, wearable technology is continuously evolving. However, similar to several technologies of the past, the diffusion of wearable devices is slow. It took a considerable amount of time for wearable devices to gain widespread acceptance in the market. The launch of Apple watches and the entry of smartphone manufacturers (i.e. Apple and Samsung) in 2015 have transformed the wearables industry (Jung, Kim, & Choi, 2016). Transformation in wearable devices is powered by the rapid advancements in information and communication technologies and miniaturization of sensors (Kim & Shin, 2015).

Wearable devices currently in the market are equipped with sensors such as accelerometer, altimeter, gyroscope, heartrate sensor, SPO2 sensor, pulse oximeter, thermometer, and GPS. These devices allow users to track various health and fitness parameters: steps taken, distance traveled, speed, elevation climbed, exercise, heartrate, ECG/EKG, oxygen saturation (SPO2), stress level, sleep patterns, calories consumed vs. calories expended, and temperature (Lin, Chou, Tsai, Lin, & Lee, 2016). The combination of sensors and monitoring capabilities varies across the models and types. Monitoring and tracking capabilities offered by wearable devices facilitate individuals to maintain a healthy lifestyle.

Sedentary lifestyle is becoming increasingly common, and the major concern here is that it is causing several health-related complications. Continuously tracking the physical activity and calories intake can motivate individuals to alter exercise routines and eating habits to promote a healthy lifestyle (Cheung et al., 2020). Similarly, falling/undetected falls, particularly for the elderly, is a crucial health issue that can result in severe negative consequences. Fall detection features in smartwatches can aid in timely detection and alerting of caretakers if a fall is detected (Mrozek, Koczur, & Małysiak-Mrozek, 2020). Approval of medical-grade ECG in wearable devices expanded its scope in healthcare (Sergueeva et al., 2020). Tracking physical activities and monitoring vital signals (heartrate, ECG\EKG) has been found to be beneficial for patients with chronic conditions (Tsai, Lin, Chang, Chang, & Lee, 2020). People with diabetes have a high risk of developing foot disease. The smart shoe insole is a wearable device which collects the parameters related to foot health and provides vital information for patients with diabetes which will help them maintaining their foot health (Macdonald, Perrin, Hyett, & Kingsley, 2019). Overall, wearable devices are promising in that they are a means of promoting the health and fitness of the population.

## 2.2 Theoretical background and hypothesis development

Early research on wearable devices focused on design aspects (Jones, Marsden, Mohd-Nasir, Boone, & Buchanan, 1999; Jung et al., 2016), on exploring the application of sensors in detecting body movements (Sazonov, 2014), and on surveying wearable devices in the market (Seneviratne et al., 2017). The studies also focused on evaluating the precision and accuracy of activity detection in wearable devices (Düking, Fuss, Holmberg, & Sperlich, 2018). As the wearable device started gaining market traction, research focus shifted towards understanding the adoption and diffusion of wearable technologies in society at large. Many scholars have investigated the adoption of different types of wearable devices, namely wearable computers (Su & Gururajan, 2010), smartwatches (Beh et al., 2021; Kim & Shin, 2015), fitness trackers (Vongurai, 2020), health wearables (Binyamin & Hoque, 2020), and smart shoe insole (Macdonald et al., 2019).

A variety of theoretical frameworks such as theory of planned behavior (TPB), technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), diffusion of innovation (DOI), protection motivation theory (PMT), privacy calculus theory (PCT), expectation confirmation theory (ECT) and behavioral response theory (BRT) have been used to understand the adoption of wearable devices. Many scholars employed the TAM or UTAUT as base models and extended them with the external or contextual factors derived from different theories. Based on the foundations laid by previous meta-analyses (Wu & Lederer, 2009; Sarkar, Chauhan, & Khare, 2020), and the theoretical frameworks of TAM, UTAUT, and the integrated conceptual model, we propose hypotheses for wearable adoption (Figure 1).

## 2.3 TAM

The Technology Acceptance Model (TAM) developed by Davis (1989) is well-known, powerful, and most influential; yet, it is one of the most parsimonious models used for explaining the adoption of technology by the users (Zhao, Ni, & Zhou, 2018). TAM is parsimonious in the sense that it uses two constructs - perceived usefulness (PU) and perceived ease of use (PEOU) to predict the attitude (ATT) and behavior intention (BI).

TAM has been used to understand the adoption of technologies ranging from information technology (Davis, 1989) to contact tracing apps for COVID 19 (Velicia-Martin, Cabrera-Sanchez, Gil-Cordero, & Palos-Sanchez, 2021); wearable devices are no exception. Prior studies have investigated the impact of the perceived usefulness, perceived ease of use, and attitude on behavioral intention to adopt wearable devices. In this study, we investigate the TAM relationships using meta-analysis to summarize findings from multiple studies.

***Perceived usefulness***

Perceived usefulness is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989). Prior studies have consistently established perceived usefulness as the significant predictor of attitude to embrace wearable devices (Sabbir, Akter, Khan, & Das, 2020; Kim & Shin, 2015). In literature, perceived usefulness also emerged as a significant predictor of behavioral intention to adopt wearable devices (Chau et al., 2019; Park et al., 2016). Cheung et al. (2020), in their research on acceptance of wearable health technology, found perceived usefulness as the strongest predictor of behavioral intention. Despite the consensus, a few studies (Tsai et al., 2020) have reported non-significant relationship between perceived usefulness and behavioral intention. However, even in those studies, perceived usefulness was indirectly influencing behavioral intention through attitude. Hence, it can be concluded that perceived usefulness is the crucial factor for the adoption of wearable devices. Studies have argued that marketers should enhance the functionality of the wearable technologies by introducing advanced monitoring features to better consumer’s health and fitness (Lai & Huang, 2018). The role of perceived usefulness in creating a positive attitude towards wearable technology is found to be significant across the board. Thus, we propose the following hypothesis:

$H_{TAM}1$: Perceived usefulness is positively related to attitude towards wearable devices for health and fitness.

$H_{TAM}2$: Perceived usefulness is positively related to behavioral intention to use wearable devices for health and fitness.

***Perceived ease of use***

Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). Many scholars have investigated the impact of perceived ease of use in predicting perceived usefulness. However, the results are mixed. Some studies found this relationship as significant (Papa et al., 2020; Park et al., 2016), while others found it to be non-significant (Vongurai, 2020; Chang et al., 2016). The studies that found this relationship to be significant, posited that perceived ease of use can be improved by designing simple interfaces, easily accessible mobile apps, tutorial videos, and user guides (Lunney, Cunningham, & Eastin, 2016). On the other hand, the studies that found this relationship as non-significant, opined that young users quickly embrace wearable technologies with ease (Cheung et al., 2020). Further, it was argued that wearable device interfaces resemble mobile phones. Owing to the familiarity with mobile devices, access to wearable devices becomes easier (Baudier, Ammi, & Wamba, 2020). The relationship between perceived ease of use and attitude also received a mixed response in the literature (Tsai et al., 2020; Baudier et al., 2020). Thus, we propose the following hypothesis:

$H_{TAM}3$: Perceived ease of use is positively related to the perceived usefulness of wearable devices.

$H_{TAM}4$: Perceived ease of use is positively related to attitude towards wearable devices for health and fitness.

***Attitude***

Attitude refers to "an individual's positive or negative feelings in performing a target behavior" (Davis, 1989). Studies that investigated the relationship between attitude and behavioral intention have consistently found this relationship to be significant (Cavdar Aksoy, Kocak Alan, Tumer Kabadayi, & Aksoy, 2020; Sabbir et al., 2020) . Studies have argued that users will develop a positive attitude when they are convinced of the usefulness (Sabbir et al., 2020) and result demonstrability of the wearable devices in improving health and fitness. The correlation between positive attitude and the intention to use is well established for wearable devices. Surprisingly, Lunney et al. (2016) studied the adoption of fitness technology and found the relationship between attitude and behavioral intention to be non-significant. However, the coefficient of this relationship is positive, and the study argued that the positive attitude leads to the behavior to adopt fitness wearables. Thus, we propose the following hypothesis:

$H_{TAM}5$: Attitude is positively related to behavioral intention to use wearable devices for health and fitness.

## 2.4 UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced by Venkatesh, Morris, Davis, & Davis (2003), synthesizing eight theories on acceptance and use of technology. Ever since its introduction, the UTAUT model has been widely used in IS/IT literature to explain technology acceptance by individuals. In UTAUT, behavior intention is explained by using the four core constructs: performance expectancy, effort expectancy, social influence, and facilitating condition. Performance expectancy and effort expectancy represents the characteristics of technology (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019). Several studies have established UTAUT as a suitable framework for explaining the adoption of wearable technologies. In this study, we investigate the original UTAUT relationships using a meta-analysis framework.

***Performance expectancy***

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). Studies have consistently reported a significant relationship between performance expectancy and behavioral intention (Beh et al., 2021; Talukder et al., 2020). Findings of Reyes-Mercado (2018) and Beh et al. (2021) projected performance expectancy as the strongest predictor of behavioral intention. Studies have argued that performance expectancy can be enhanced by incorporating advanced health monitoring functionalities (Sergueeva & Shaw, 2017), facilitating continuous monitoring of health and fitness parameters and integrating wearable devices with the healthcare service providers (Talukder et al., 2020). Thus, we propose the following hypothesis:

$H_{UTAUT}1$: Performance expectancy is positively related to behavioral intention to use wearable devices for health and fitness.

***Effort expectancy***

Effort expectancy is defined as “the degree of ease associated with the use of the system” (Venkatesh et al., 2003). In the wearable device context, many studies (Reyes-Mercado, 2018; Sergueeva & Shaw, 2017) found a significant relationship between effort expectancy and behavioral intention; though a few studies (Binyamin & Hoque, 2020; Talukder et al., 2020) did report non-significant results. Studies that supported this relationship posited that minimizing the effort required to operate the wearable devices enhances adoption. Scholars have argued that designing intuitive, user-friendly interfaces, providing tutorials, user manuals, and creating support infrastructure would minimize the effort required (Reyes-Mercado, 2018). Counter-arguments stated that wearable devices require bare minimum effort, automated alerts, prior experience with smartphones, and easy access to social media enable users to operate the wearable devices quite easily (Binyamin & Hoque, 2020). We propose the following hypothesis:

$H_{UTAUT}2$: Effort expectancy is positively related to behavioral intention to use wearable devices for health and fitness.

***Facilitating condition***

Facilitating condition is defined as “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003). Many studies that investigated the relationship between facilitating condition and behavioral intention in the wearable device context found it to be significant (Wang, Tao, Yu, & Qu, 2020; Li, Ma, Chan, & Man, 2019). Binyamin & Hoque (2020), in their study on the adoption of wearable health technology, found facilitating condition as the strongest predictor of behavioral intention. However, few studies also reported non-significant results (Macdonald et al., 2019; Talukder et al., 2020). Studies that favored this relationship indicated that effective utilization of wearable devices requires access to resources such as smartphones, mobile apps, wi-fi, and bluetooth (Wang et al., 2020). Interestingly, studies have also highlighted the role of practitioners and family members in enabling these resources for older adults ( Li et al., 2019). Counter-arguments pointed that individuals, including older adults, are equipping themselves to use wearable devices through the support of social media and web-based tutorials (Talukder et al., 2020). We propose the following hypothesis:

$H_{UTAUT}3$: Facilitating condition is positively related to behavioral intention to use wearable devices for health and fitness.

***Social influence***

Social influence is defined as “the degree to which an individual perceives that it is important for others to believe that he or she should use the new system” (Venkatesh et al., 2003). The relationship between social influence and behavioral intention received mixed results in the literature. While some studies found this relationship as significant (Wang et al., 2020; Gao et al., 2015), other studies exhibited non-significant relationships (Beh et al., 2021; Reyes-Mercado, 2018). Individuals are more likely to use wearable devices when people important to them in their social circle (family, colleagues, and friends) use them or endorse them. Studies have highlighted three options for creating favorable social influence. Firstly, understanding the motive for people to use wearable devices and incorporating them in wearable design (Wang et al., 2020). Secondly, creating forums that facilitate interaction within the social circle. Finally, utilizing the forums to discuss best practices and organize competitions that can maximize wearable devices' utility (Binyamin & Hoque, 2020). Contrary to that, social influence was found to be non-significant in two circumstances - first, when early adopters embraced wearable technology (Reyes-Mercado, 2018); second, when wearable devices are adopted solely for healthcare purposes (Beh et al., 2021). We propose the following hypothesis:

$H_{UTAUT}4$: Social influence is positively related to behavioral intention to use wearable devices for health and fitness.

## 2.5 Integrated conceptual model

The integrated conceptual model is developed to bring a holistic perspective to the adoption of wearable devices. Based on the popularity, usage frequency, and relevance of wearable technology, nine constructs were included in the model to measure behavioral intention. Four constructs, namely perceived usefulness, perceived ease of use, attitude, social influence, were drawn from TAM and UTAUT. We also included five contextual and external variables: compatibility, innovativeness, self-efficacy, perceived privacy risk, and price value. However, some of the relevant constructs connected to health-related behavior such as health belief, trust, and health risk were not considered as they have been investigated in fewer than the required number of studies needed for meta-analysis. To develop an integrated perspective, constructs with similar meanings have been grouped. As illustrated in Table 1, all the TAM and UTAUT constructs have been absorbed in the integrated conceptual model.

**Table 1. Variables grouping logic**

| Construct | Constructs with similar meaning | Supporting literature |
|---|---|---|
| Perceived usefulness | Performance expectancy | Dwivedi, Rana, Chen, & Williams, 2011; Zhao et al., 2018 |
| Perceived ease of use | Effort expectancy, Perceived convenience | Dwivedi et al., 2011; Zhao et al., 2018 |
| Social influence | Subjective norm | Zhao et al., 2018 |
| Innovativeness | Personal innovativeness, Consumer innovativeness | Zhao, Li, & Zhang, 2019 |
| Price value | Cost | Beh et al. (2021) |
| Self-efficacy | Facilitating condition, Perceived behavioral control | Zhao et al., 2018 |

Based on the review of literature presented earlier for TAM and UTAUT frameworks, the following hypotheses have been derived for the integrated conceptual model:

$H_{ICM}1$: Perceived usefulness is positively related to attitude towards wearable devices for health and fitness.

$H_{ICM}2$: Perceived usefulness is positively related to behavioral intention to use wearable devices for health and fitness.

$H_{ICM}3$: Perceived ease of use is positively related to the perceived usefulness of wearable devices.

$H_{ICM}4$: Perceived ease of use is positively related to attitude towards wearable devices for health and fitness.

$H_{ICM}5$: Perceived ease of use is positively related to behavioral intention to use wearable devices for health and fitness.

$H_{ICM}6$: Attitude is positively related to behavioral intention to use wearable devices for health and fitness.

$H_{ICM}7$: Social influence is positively related to behavioral intention to use wearable devices for health and fitness.

The DOI theory proposed by Rogers (1983) was used to understand the innovation trajectory, factors causing the wider dissemination in society, and innovation success. DOI postulates that diffusion of innovation is dependent on the innovativeness of the individuals adopting it. Constructs such as innovativeness and compatibility derived from DOI (Agarwal & Prasad, 1998) have been used to explain the adoption of wearable devices.

***Innovativeness***

Innovativeness is defined as "the degree to which a person is earlier than other social members in adopting new technology" (Rogers, 1983). Several studies that investigated the relationship between innovativeness and behavioral intention found it significant (Asadi et al., 2019; Park et al., 2016). Studies have highlighted that an individual with high innovativeness is more likely to adopt wearable devices. Further, studies argued that marketers should create awareness about the innovative features available in wearable devices. Zhang et al. (2017) investigated the adoption of healthcare wearables and stated that males possessed higher innovativeness in adopting wearable technology. They also suggested introducing novel features targeted at male consumers and encouraging consumers with higher innovativeness (males) to share the information for enhancing the adoption by consumers with low innovativeness. We propose the following hypothesis:

$H_{ICM}8$: Innovativeness is positively related to behavioral intention to use wearable devices for health and fitness.

***Compatibility***

Compatibility is defined as "the degree to which a technology complies with the technical functionalities of other existing products" (Bradford & Florin, 2003). The relationship between compatibility and behavioral intention to adopt wearable devices is strongly supported in the literature ( Li et al., 2019; Rajanen & Weng, 2017). Compatibility of wearable devices with the user's lifestyle and other communication devices significantly influenced the adoption. Li et al. (2019) prescribed the designing of lightweight, elegant, and easy to wear devices that can be compatible with the lifestyles of older adults. We propose the following hypothesis:

$H_{ICM}9$: Compatibility is positively related to behavioral intention to use wearable devices for health and fitness.

***Self-efficacy***

According to the self-efficacy theory proposed by Bandura (1977), self-efficacy refers to "the degree to which the individual believes that they have the skills to adopt a wearable device." Self-efficacy is used to study the behavior and motivation to perform a specific activity. Scholars have employed self-efficacy to study the impact of device efficacy on the adoption intention of wearable devices (Macdonald et al., 2019; Sergueeva & Shaw, 2017). Mixed findings have emerged for this relationship. Macdonald et al. (2019), who studied the adoption of smart shoe insole argued that self-efficacy is a vital factor when the technology is first presented to the individuals. Gao et al. (2015) found self-efficacy as a significant predictor for fitness wearables and non-significant for medical wearables. Sergueeva & Shaw (2017) claimed self-efficacy as a non-significant predictor of healthcare wearables. They reflected that consumers gain confidence and the ability to use wearable devices from easily accessible mobile applications. We propose the following hypothesis:

$H_{ICM}10$: Self-efficacy is positively related to behavioral intention to use wearable devices for health and fitness.

***Perceived privacy risk***

Given the sensitive nature of health information measured in wearable devices, privacy becomes an essential element (Gao et al., 2015). Scholars (Adebesin & Mwalugha, 2020; Niknejad, Hussin, Ghani, & Ganjouei, 2020) have employed PCT to study the negative impact of perceived privacy risk in the adoption of wearable devices. While most studies found this relationship to be significant (Adebesin & Mwalugha, 2020; Choi, Hwang, & Lee, 2017), few studies did reveal non-significant relationship (Sergueeva et al. 2020). Studies have postulated that robust privacy policies (Niknejad et al., 2020), developing regulations that can guide wearable device manufacturers in data acquisition, and mechanisms to handle incidents of privacy intrusion can promote the adoption of wearable technology. Contrarily, Scott (2020) argued that while privacy is important, it cannot act as a limiting force in the adoption of wearable technology. We propose the following hypothesis:

$H_{ICM}11$: Perceived privacy risk is negatively related to behavioral intention to use wearable devices for health and fitness.

***Price value***

Price value (PV) is defined as the "consumer's cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh, Thong, & Xu, 2012). Scholars who investigated the impact of price value on the adoption of wearable devices found mixed results. Interestingly most studies found this relationship as non-significant (Beh et al., 2021; Talukder et al., 2019). However, a few studies reported significant findings (Park, 2020; Kim & Shin, 2015). Beh et al. (2021) indicated that wearable devices are available at different price levels, and the users are free to choose the device which meets their budgets. It has also been argued that the price value is non-significant because users are ready to devote their financial resources to monitor health and fitness and improve health conditions (Talukder et al., 2019). We propose the following hypothesis:

$H_{ICM}12$: Price value is positively related to behavioral intention to use wearable devices for health and fitness.

***Culture as a moderator***

In this study, we chose to investigate the cultural differences in the adoption of wearable devices for two reasons: Firstly, this study attempted to respond to the numerous calls made in the literature to investigate cultural impacts on the antecedents of behavioral intention to adopt wearable devices. Gastaldi, Lettieri, & Mandolfo (2019) advocated a deeper examination of cultural impact on the adoption of wearable technologies. Many other studies have also articulated the need to conduct cross-cultural analysis on the acceptance of wearable technologies (Niknejad et al., 2020; Kim & Shin, 2015), and have recommended cross-cultural studies on wearable devices to account for social factors (Zhang et al., 2017), cultures with varying economic conditions (Chau et al., 2019), and varying acceptance levels of technology (Beh et al., 2021). Baudier et al. (2020) investigated the adoption of smartwatches in the developed nations (the USA, UK, Germany, and France) and reflected the need for future studies to consider the Asian continent. Secondly, prior meta-analysis studies have successfully validated the differing impact on the antecedents of technology adoption across eastern and western cultures (Mehta et al., 2021; Schepers & Wetzels, 2007). Hence, we have investigated the cultural differences in eastern and western cultures in the context of wearable devices.

Culture plays a vital role in shaping, controlling, and influencing various human endeavors. Hofstede (2001) cultural dimension is the widely used theoretical framework to understand cross-cultural differences. Four key dimensions - individualism/collectivism, masculinity/femininity, power distance, and uncertainty avoidance, have been used in the IS literature to understand the impact of cultural dimensions in technology adoption (McCoy, Everard, & Jones, 2005). In IS literature, Srite & Karahanna (2006) conceptualized the moderating role of culture in technology adoption. They successfully established the cultural impact on TAM relationships from the context of information technology development. Further, differences in cultural dimensions causing differing effects on technology adoption is well established in the literature (Tarhini, Hone, Liu, & Tarhini, 2017).

Western cultures symbolize individualism in the individualism/collectivism dimension, and eastern cultures represent collectivism (Hofstede, 2011). Individualism in the cultural context, typically focuses on individual goal achievement. For this reason, prior studies have hypothesized that culture could moderate the relationship between perceived usefulness and behavioral intention (Tarhini et al., 2017). In the context of wearable devices, an individuals' goal-directed behavior will enable them to utilize wearable technologies to meet their health objectives effectively. Thus, culture could have a moderating impact on the relationship between perceived usefulness and the behavioral intention to use wearable devices. Collectivist cultures provide due importance to the voice of social reference groups. Their opinions and suggestions could significantly influence the behavior of the individuals. Thus, we may expect culture to moderate the relationship between social influence and adoption of wearable devices. Prior studies on adoption of wearable devices supported this divergence. For instance, many studies conducted in the eastern countries found the relationship between social influence and behavioral intention to be significant (Talukder et al., 2020; Gao et al., 2015), while some studies conducted in the western culture found it as non-significant (Reyes-Mercado, 2018; Patton, 2018).

Prior research indicates that learnings in collectivist cultures happen in a group. Typically, collectivism cultures tend to possess low self-efficacy (Earley, 1994). Recent research on technology adoption has confirmed that culture could moderate the relationship between self-efficacy and behavioral intention (Zhao, Wang, Li, Zhou, & Li, 2021). Further, the study also confirmed the high impact of self-efficacy in a collectivist culture. Several studies that investigated the adoption of wearable devices in the eastern culture found a significant impact of self-efficacy on adoption ( Kim & Ho, 2021; Beh et al., 2021).

Western cultures characterize masculinity in the Masculine/Feminine dimension, and eastern cultures portray femininity (Hofstede, 2011). Feminine cultures emphasize the quality of life, and they expect pleasant experience in their activities. We may expect that feminism cultures typically emphasize wearable devices that are easy to use. Prior studies on the adoption of wearable devices found divergent results. Many studies in the eastern context found the relationship between perceived ease of use and behavioral intention as significant (Talukder et al., 2019; Reyes-Mercado, 2018), while studies in the western context found it to be non-significant (Blumenthal, Wilkinson, & Chignell, 2018; Choi et al., 2017).

Masculine culture is also characterized as competitive and associated with acquiring new technology. Prior studies on technology adoption have hypothesized that culture could moderate the relationship between innovativeness and behavioral intention (Zhao et al., 2021). We may expect that the individuals from masculinity cultures possess high innovativeness in adopting the latest wearable devices equipped with advanced monitoring capabilities. Masculinity cultures also influence in converting the attitude to behavioral intention (Alshare, Mesak, Grandon, & Badri, 2011) to use wearable devices. Overall, we propose the following hypothesis:

$H_{ICM}$13: Culture moderates the relationship between the antecedents of behavioral intention to use wearable devices for health and fitness.

***User type as a moderator***

Prior research on the adoption of wearable devices has focused on two types of individuals: users and non-users. There is a significant gap in understanding how the antecedents of wearable devices differ between users and non-users. Non-users would have a vague idea about wearable technology. They may not be aware of how the different functionalities in the wearable devices will work in real-time. However, users' perspective about wearable devices is shaped by the experience gained by using the product. Users would be aware of the utility of the devices in meeting the health and fitness goals, whereas non-users only speculate on these matters.

Technology adoption research focusing on emerging technologies such as wearable devices from both user's and non-user's perspectives provides important implications for practice. Understanding the user's adoption facilitates the practitioners to understand the factors enabling them to use it after purchase. Manufacturers can push new features through software updates to meet user demand and maximize the utility of the product. Non-users could be potential buyers of wearable devices. From the non-users, practitioners can gain rich insights into the expectation of prospective users. Accordingly, they can introduce new designs and features into the next-generation wearable devices. Many studies on the adoption of wearable devices have focused only on the users, whereas fewer studies have considered respondents as non-users. Implications from user-based studies would not apply to the non-user studies (Choi & Song, 2020). Moreover, studies investigating the differential impact of users and non-users are currently lacking in this context. For these reasons, we investigate the moderating role of user type (users, non-users) in the adoption of wearable devices.

Comparison of results from the prior studies indicates the differential impacts between users and non-users among the antecedents of wearable device adoption. For instance, all the non-user-based studies have reported a significant relationship between perceived ease of use and perceived usefulness ( Li et al., 2019; Zhang et al., 2017). At the same time, a few user-based studies have reported non-significant results (Lai & Huang, 2018). Non-users may think that wearable devices should be easy to use. However, once when they start using the devices, they get accustomed to it. Prior studies observed the sharp differences in the social influence to adopt wearable devices between the user types. Surprisingly, all the non-user-based studies that investigated the relationship between social influence and behavioral intention found it non-significant (Li et al., 2019; Reyes-Mercado, 2018). Many user-based studies found this relationship to be significant (Talukder et al., 2020; Gao et al., 2015). This implies that social influence is driving the adoption of wearable devices among users. Divergent conclusions have emerged for the relationship between self-efficacy and behavioral intention. These relationships were significant for all the non-user-based studies (Li et al., 2019; Reyes-Mercado, 2018), while a few user studies have reported non-significant relationships (Talukder et al., 2020; Gao et al., 2015). Certain relationships are found to be significant in both user groups. For instance, the relationship between perceived usefulness and behavioral intention and the relationship between perceived usefulness and attitude were significant in both groups. Yet, differences in impact sizes in these relationships needs to be investigated. Based on the above arguments, we propose the following hypothesis:

$H_{ICM}14$: User type moderates the relationship between the antecedents of behavioral intention to use wearable devices for health and fitness.

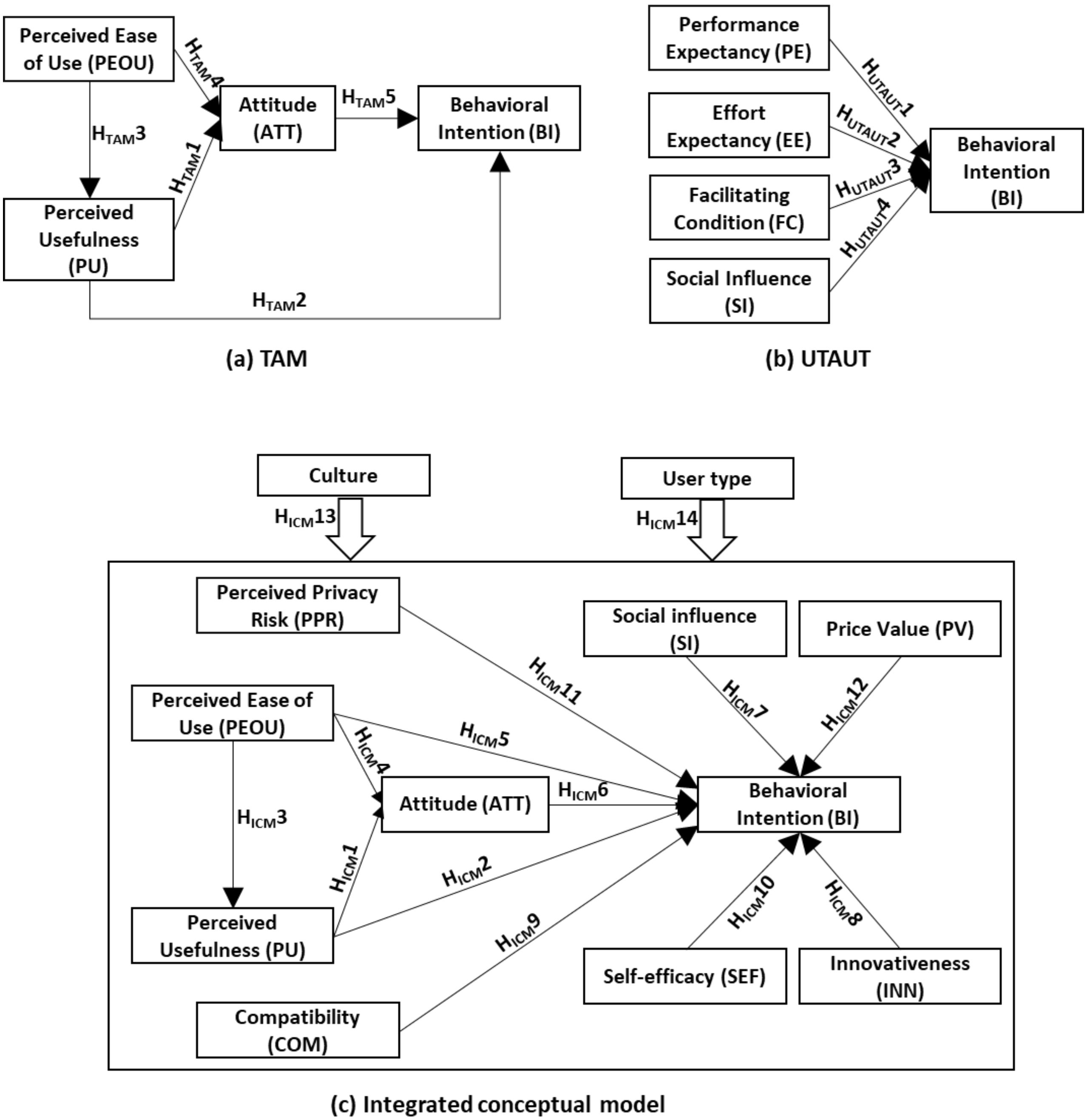


**Figure 1. Research Model**

# 3 Methods

## 3.1 Literature search and study selection

The meta-analysis framework used in this study was adopted from the previous studies (Sarkar et al., 2020; Wu & Lederer, 2009). We adopted three search strategies to identify the potential articles for the meta-analysis. First, according to the meta-analysis principles, this study considered research articles from various sources, including journals, book chapters, conference proceedings, and doctoral dissertations. A systematic search of the literature was conducted with the following databases: Scopus, Elsevier, Web of Science, Science Direct, and IEEE explore. We manually searched the popular IS conference databases (i.e., International Conference on Information System (ICIS), European Conference on Information Systems (ECIS), Americas Conference on Information Systems (AMCIS), Hawaii International Conference on Information Systems Sciences (HICSS), and the Pacific Asia Conference on Information Systems (PACIS) for proceedings. Secondly, the meta-analysis needs to include both published and unpublished materials. Unpublished documents were sourced from Google scholar; unpublished dissertations were searched for in the ProQuest database for dissertation and thesis. Search terms used in this analysis are shown in Table 2. All three types of keywords were connected using the "AND" operator to generate search strings. Finally, forward tracking and backtracking approaches were employed to search the citations (google scholar) and references of the selected articles to locate the missing studies. The article search was conducted between 9$^{th}$ April to 15$^{th}$ April 2021. The publishing year for the chosen articles ranged from 2015 to 2021.

## 3.2 Inclusion and Exclusion criteria

The studies included met the following criteria: 1) they were empirical investigations, 2) they examined the context: adoption of wearable devices for health and fitness, 3) they included at least one relationship from the TAM, UTAUT, or integrated conceptual model, 4) they reported sample size and correlation coefficient. Studies that investigated the adoption of wearable devices from contexts other than health and fitness were not considered.

Articles were carefully screened according to the predefined criteria. The study selection process and the details of the inclusion and exclusion criteria were applied in each step; they are illustrated in Figure 2. Initial literature searches from various academic databases resulted in 2027 articles. After removing duplicates, 1681 unique records were qualified for further screening. In the next step, we manually screened the title, abstracts, and keywords by applying inclusion criteria to identify the potential articles. Qualitative studies, editorials, commentaries, and articles written in languages other than English were also removed in this step. Finally, full texts of 103 articles were assessed for inclusion. In this step, we excluded the articles that have not investigated the hypothesized relationships (n=5), not focused on health and fitness context (n=15), and articles that failed to report metrics needed to perform meta-analysis (i.e., sample size, correlation coefficient, etc.) (n=25) and qualitative investigations (n=7). Articles which reported the results of two independent empirical investigations were treated as two separate studies. Based on the selection criteria, a total of 56 studies were selected from 52 articles for inclusion in the meta-analysis. The final sample comprises research articles (n=44), conferences and book chapters (n=7), and Ph.D. dissertations (n=5).

**Table 2. Search terms**

| Type | Theme | Keywords |
|---|---|---|
| 1 | Wearable | Wearable devices, wearable technologies, smartwatch, fitness band, fitness tracker, heart rate monitor, smart clothes, foot shoe insole |
| 2 | Adoption | Behavioral intention, adoption intention, intention to use, attitude, adoption, acceptance |
| 3 | Health | Health, fitness |

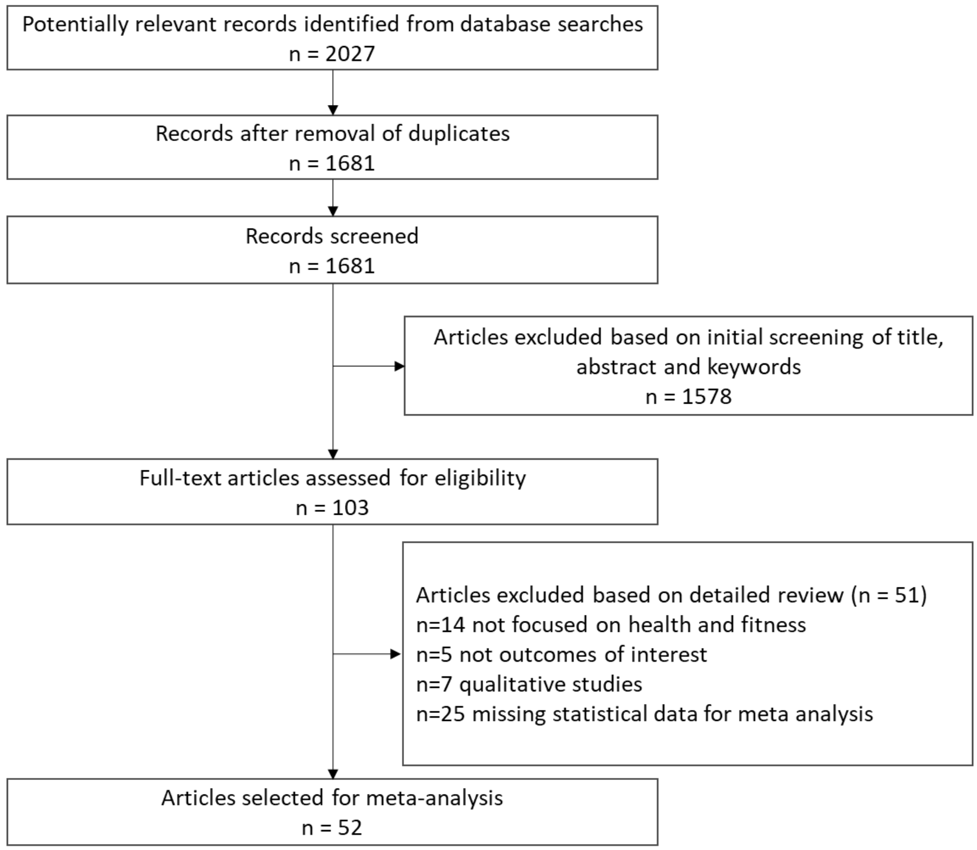


**Figure 2. Study selection process**

## 3.3 Coding procedure

First, the study coding involved extracting study characteristics, including the author, sample size, sample nationality, user type, population, and theory base. Table 3 provides detailed information about the 56 empirical studies identified from the 52 articles. Second, the statistics necessary for the meta-analysis, including the effect sizes between the critical constructs and construct reliability (Cronbach's α and composite reliability) were extracted.

The standard practice uses the correlation coefficient as an effect size in the meta-analytical studies (Sarkar et al., 2020). Unlike the path coefficient (β), the correlation coefficient (r) is not affected by the impacts of other independent variables. Hence, correlation is the robust measure of direct impact between the two variables. For this reason, this study considered correlation coefficient value as effect size.

For the purpose of analysis, studies conducted with different samples (e.g., users and non-users) were treated as separate studies. The constructs, relationships, and effect sizes were directly taken for the meta-analysis conducted on TAM and UTAUT frameworks. However, similar constructs have been grouped in study coding (as elaborated in the research model) for meta-analysis conducted on the integrated conceptual framework. The studies were classified based on country of origin (Eastern, Western, and others) and user type (users of the wearable device and non-users) to facilitate moderator analysis.

The coding procedure was conducted objectively. Correlation and reliability data were meticulously captured from the articles. Based on the country of origin of the sample, studies performed in North and South America, Europe, Australia, and New Zealand were grouped as western culture, and the remaining countries were grouped as eastern culture (Mehta et al., 2021; Schepers & Wetzels, 2007). Similarly, based on the user type, studies were classified as users (entire study sample comprised of users), non-users (entire study sample comprised of non-users), and others (study sample include both users and non-users). The two researchers independently carried out the coding procedure for the whole study. The third researcher reviewed the coded data to assess the reliability. Owing to the objective nature of coding, the inter-rater reliability between the first two researchers was estimated to be high with 98.5%. There were very few discrepancies, and these were resolved through discussion and mutual consensus.

## 3.4 Data analysis

In accordance with the three models incorporated in this study, we computed the descriptive statistics for each of the pairwise relationships from the selected 56 studies. Descriptive statistics showed the rate of significant relationships and their importance in the adoption of wearable devices. The reliability statistics of each construct were also analyzed to establish the stability and consistency of the proposed integrated conceptual model.

Meta-analysis was used to analyze the effect size from multiple studies to determine the combined effect size. Fixed and random-effects models were the two models available for conducting the meta-analysis. The random-effects model assumes that the effect sizes will vary across the population and tries to capture this variation. This study considered a random effect size to account for the heterogeneity of the effect sizes across the studies.

The measurement error and sampling error-corrected weighted cumulative effect size for each pair-wise relationship was calculated as, $r_+ = \frac{\sum N_i r_i}{\sum N_i}$, where $r_+$ is the mean corrected effect size, $r_i$ is the effect size of study i, and $N_i$ is the sample size of study i. We conducted the fisher z transformation of the effect sizes as, $z_+ = \frac{\sum z_i r_i}{\sum z_i}$, and weighted mean z was calculated by considering the sample size as, $z_+ = \frac{\sum z_i r_i}{\sum z_i}$. The cumulative effect size was then computed using the inverse z transformation. The 95% confidence interval was calculated for each of the pairwise relationships included in the study. Heterogeneity across the studies was tested using the Q-statistic and $I^2$ estimates. Q-statistic investigates the null hypothesis that all studies have a similar effect size. Rejection of the null hypothesis confirmed the presence of heterogeneity and justified the selection of the random-effects model. The $I^2$ statistic, on the other hand, measures the rate of heterogeneity present across the studies. $I^2$ values of 25%, 50%, and 75% represent the presence of low, moderate, and high heterogeneity (Higgins & Thompson, 2002). Generally, $I^2$ values greater than 60% are considered significant.

The conceptual model proposed in the study integrated the core theories on technology adoption; apart from this, the model also considered the constructs that are critical for the adoption of wearable devices. We did a moderator analysis based on the integrated conceptual framework. The culture and user type were the categorical moderators tested in this study. We calculated the combined effect size and Q statistic for each of the pairwise relationships. The significance of the Q-value indicated the presence of a moderating effect.

Publication bias is the tendency of the investigators to report the positive findings and ignoring the non-significant results (Egger, Smith, Schneider, & Minder, 1997). It is important to assess the presence of publication bias in the meta-analytic investigations. This paper employed Egger's regression test to examine the potential publication bias. Both the meta-analysis and the moderator analysis were performed using the Comprehensive Meta-Analysis Version 3.

**Table 3. Study characteristics**

| Author | Sample Size | Country | Culture | User Moderator | Article type | Theories used |
|---|---|---|---|---|---|---|
| Dai, Larnyo, Tetteh, Aboagye, & Musah (2020) | 350 | Africa | Eastern | General | J | Extended UTAUT |
| Sabbir et al. (2020) | 300 | Bangladesh | Eastern | General | J | Extended TAM |
| Talukder et al. (2020) | 325 | China | Eastern | Users | J | Extended UTAUT2 |
| Wang et al. (2020) | 406 | China | Eastern | General | J | UTAUT and TTF |
| Talukder et al. (2019) | 392 | China | Eastern | Users | J | UTAUT2 and DOI |
| Li et al. (2019) | 146 | China | Eastern | Non-User | J | TAM and UTAUT |
| Zhang et al. (2017) | 197 | China | Eastern | Non-User | J | TAM and HBM |
| | 239 | China | Eastern | Non-User | J | TAM and HBM |
| Rajanen & Weng (2017) | 156 | China | Eastern | General | C | TAM and DOI |
| Li, Wu, Gao, & Shi (2016) | 333 | China | Eastern | Users | J | PCT |
| Gao, Zhang, & Peng (2016) | 145 | China | Eastern | Users | C | TAM and IDT |
| Gao et al. (2015) | 232 | China | Eastern | Users | J | UTAUT2, PMT and PCT |
| | 230 | China | Eastern | Users | J | UTAUT2, PMT and PCT |
| Cheung et al. (2020) | 211 | Hong Kong | Eastern | Users | J | Extended TAM |
| Cheung et al. (2019) | 171 | Hong Kong | Eastern | Users | J | TAM and HBM |
| Chau et al. (2019) | 171 | Hong Kong | Eastern | Users | J | Extended TAM |
| Kim (2016) | 200 | Hong Kong | Eastern | Users | J | Extended TAM |
| Papa et al. (2020) | 273 | India | Eastern | Users | J | Extended TAM |
| Sivathanu (2018) | 815 | India | Eastern | Users | J | Extended BRT |
| Adebesin & Mwalugha (2020) | 232 | Kenya, South Africa | Eastern | General | J | Trust propensity |
| Kim & Chiu (2019) | 247 | Korea | Eastern | Users | J | TAM and TR |
| Park (2020) | 1380 | Korea | Eastern | Users | J | TAM and ECT |
| Chang et al. (2016) | 342 | Korea | Eastern | General | J | TAM and TTF |
| Niknejad et al (2020) | 100 | Malaysia | Eastern | Users | J | Extended UTAUT2 |
| Beh et al. (2021) | 271 | Malaysia | Eastern | General | J | Extended UTAUT2 |
| Asadi et al. (2019) | 178 | Malaysia | Eastern | Users | J | TAM and DOI |
| Binyamin & Hoque (2020) | 256 | Saudi Arabia | Eastern | Users | J | Extended UTAUT2 |
| Lazaro, Lim, Kim, & Yun (2020) | 76 | South Korea | Eastern | General | C | Extended TAM |
| Park et al. (2016) | 877 | South Korea | Eastern | Users | J | Extended TAM |
| Kim & Shin (2015) | 362 | South Korea | Eastern | Users | J | Extended TAM |
| Kim & Ho (2021) | 268 | Taiwan | Eastern | General | J | UTAUT and HBM |
| Tsai et al. (2020) | 50 | Taiwan | Eastern | Non-User | J | TAM |
| | 31 | Taiwan | Eastern | Non-User | J | TAM |
| Kao, Nawata, & Huang (2019) | 226 | Taiwan | Eastern | Users | J | Extended TAM |

| | | | | | | |
|---|---|---|---|---|---|---|
| Lai & Huang (2018) | 120 | Taiwan | Eastern | Users | C | Extended TAM3 |
| Lin et al. (2016) | 50 | Taiwan | Eastern | Non-User | J | Extended TAM |
| Vongurai (2020) | 633 | Thailand | Eastern | Users | J | Extended TAM |
| Macdonald et al. (2019) | 53 | Australia | Western | General | J | UTAUT |
| Macdonald, Perrin, & Kingsley (2020) | 111 | Australia | Western | General | J | UTAUT |
| Blumenthal et al. (2018) | 76 | Canada | Western | General | J | TAM |
| Paré et al. (2018) | 580 | Canada | Western | Users | J | TAM and ECT |
| Khakurel, Immonen, Porras, & Knutas (2019) | 129 | Finland | Western | General | C | Extended UTAUT |
| Baudier et al. (2020) | 1197 | France, Germany, UK, and USA | Western | Users | J | Extended TAM |
| Gastaldi et al. (2019) | 1000 | Italy | Western | General | C | Extended TPB |
| Reyes-Mercado (2018) | 176 | Mexico | Western | Users | J | UTAUT |
| | 187 | Mexico | Western | Non-User | J | UTAUT |
| Cavdar Aksoy et al. (2020) | 411 | Turkey | Western | General | J | UTAUT |
| Robertson (2021) | 341 | US | Western | Non-User | D | UTAUT |
| Scott (2020) | 165 | US | Western | Users | D | UTAUT and PCT |
| Sergueeva et al. (2020) | 277 | US | Western | General | J | Extended UTAUT2 |
| Lahoud (2019) | 87 | US | Western | General | D | Extended TAM |
| Harmon (2019) | 256 | US | Western | Users | D | Extended UTAUT2 |
| Patton (2018) | 144 | US | Western | General | D | UTAUT2 |
| Choi et al. (2017) | 120 | US | Western | General | J | TAM and UTAUT2 |
| Sergueeva & Shaw (2017) | 141 | US | Western | General | C | Extended PMT |
| Lunney et al. (2016) | 206 | US | Western | General | J | Extended TAM |

J – Journal articles, C – Conference and book chapters, D - Dissertation

# 4 Results

## 4.1 Descriptive Statistics

Two-thirds of the studies were conducted in Eastern cultures (66%), western culture accounts for one-third (34%) of the studies. The sample included in the studies consisted of users of wearable devices (48%), non-users (15%), and the general population (37%). In terms of theory usage, 64% of the studies used at least one TAM construct, 43% of the studies used at least one UTAUT construct, and 14% of the studies used at least one construct from both the models. A few studies that employed TAM models adopted the Social Influence construct from the UTAUT model; and UTAUT studies embraced the Attitude construct from the TAM model.

A summary analysis of the relationships between the antecedents and consequences presented in Table 4 shows that the average sample size for the pair-wise relationships usually exceeded 200. It is also clear that the TAM relationships have been examined in more studies as compared to the UTAUT model. The Table also shows that the impact of perceived usefulness on behavioral intention (27 studies) was the most frequently investigated TAM relationship. The effect of social influence on behavioral intention was the most frequently used UTAUT relationship (20 studies). Also, the relationship between perceived usefulness and behavioral intention (45 studies) became the most frequently used relationship in the integrated model.

Interestingly, while comparing the TAM and UTAUT paths, it was found that there was a similarity in the percentage of significant paths between the impact of perceived usefulness on behavioral intention (85%), performance expectancy on behavioral intention (83%). The relationship between perceived usefulness and attitude (100%) was found to be significant in all the studies. The relationship between price value and the behavioral intention was the least significant (33%) relationship reported in the studies.

TAM has been criticized by many scholars, and Dwivedi et al. (2011) argued that criticism of TAM could facilitate the adoption of UTAUT. While studies using the UTAUT model are on the rise, TAM is still the most preferred model of scholars to study the acceptance of wearable technologies. Scholars have added novelty in extending the TAM model by incorporating the context-specific constructs.

**Table 4. Descriptive statistics**

| Relationship | Number of studies | Range of Correlation | Correlation | | Sample Range | | Cumulative Sample Size | Average Sample Size |
|---|---|---|---|---|---|---|---|---|
| | | | Significant (%) | Non-Significant | Lower | Upper | | |
| **TAM Model** | | | | | | | | |
| PU – ATT ($H_{TAM}1$) | 16 | 0.34-0.88 | 16 (100%) | 0 | 31 | 1197 | 6059 | 379 |
| PU – BI ($H_{TAM}2$) | 27 | 0.25–0.82 | 23 (85%) | 4 | 31 | 1380 | 8402 | 311 |
| PEOU – PU ($H_{TAM}3$) | 22 | 0.16-0.80 | 17 (77%) | 5 | 31 | 1197 | 7199 | 327 |
| PEOU – ATT ($H_{TAM}4$) | 15 | 0.16-0.80 | 11 (73%) | 4 | 31 | 1197 | 5059 | 337 |
| ATT – BI ($H_{TAM}5$) | 20 | 0.35-0.83 | 18 (90%) | 2 | 31 | 1000 | 6381 | 319 |
| **UTAUT Model** | | | | | | | | |
| PE – BI ($H_{UTAUT}1$) | 18 | 0.15-0.83 | 15 (83%) | 3 | 53 | 406 | 4345 | 241 |
| EE – BI ($H_{UTAUT}2$) | 16 | 0.13-0.79 | 12 (75%) | 4 | 53 | 406 | 3715 | 232 |
| FC – BI ($H_{UTAUT}3$) | 16 | 0.07-0.78 | 12 (75%) | 4 | 53 | 406 | 3591 | 224 |
| SI – BI ($H_{UTAUT}4$) | 20 | 0.07-0.83 | 14 (70%) | 6 | 53 | 406 | 4341 | 217 |
| **Integrated Model** | | | | | | | | |
| PU – ATT ($H_{ICM}1$) | 16 | 0.34-0.88 | 16 (100%) | 0 | 31 | 1197 | 6059 | 379 |
| PU – BI ($H_{ICM}2$) | 45 | 0.15-0.83 | 38 (84%) | 7 | 31 | 1380 | 12662 | 281 |
| PEOU – PU ($H_{ICM}3$) | 24 | 0.16-0.80 | 19 (79%) | 5 | 31 | 1197 | 7506 | 313 |
| PEOU – ATT ($H_{ICM}4$) | 14 | 0.16-0.80 | 10 (71%) | 4 | 31 | 1197 | 4759 | 340 |
| PEOU – BI ($H_{ICM}5$) | 27 | 0.13-0.79 | 17 (63%) | 10 | 53 | 580 | 6529 | 242 |
| ATT – BI ($H_{ICM}6$) | 20 | 0.35-0.83 | 18 (90%) | 2 | 31 | 1000 | 6381 | 319 |
| SI – BI ($H_{ICM}7$) | 23 | 0.07-0.83 | 17 (74%) | 6 | 53 | 572 | 5461 | 237 |
| INN – BI ($H_{ICM}8$) | 8 | 0.27-0.79 | 6 (75%) | 2 | 171 | 877 | 2280 | 326 |
| COM – BI ($H_{ICM}9$) | 4 | 0.21-0.71 | 3 (75%) | 1 | 146 | 392 | 872 | 218 |
| SEF – BI ($H_{ICM}10$) | 21 | 0.06-0.78 | 16 (76%) | 5 | 53 | 1000 | 5873 | 280 |
| PPR – BI ($H_{ICM}11$) | 14 | -0.34-0.77 | 10 (71%) | 4 | 87 | 342 | 3112 | 222 |
| PV – BI ($H_{ICM}12$) | 9 | -0.33-0.8 | 3 (33%) | 6 | 141 | 1380 | 4100 | 456 |

## 4.2 Meta-analysis

Effect sizes examined by at least three trials (Kirca, Jayachandran, & Bearden, 2005) were included in the meta-analysis. All the paths of the original TAM and UTAUT models were examined in more than three studies. Twelve path coefficients from the integrated model were included in the analysis. Table 5 summarizes the meta-analysis results and reports the combined effect size, 95% confidence interval, tests of heterogeneity, and publication bias. First, we tested the basic TAM model using its fundamental constructs, i.e., the independent variables – perceived usefulness and perceived ease of use and the dependent variables attitude and behavioral intention. Table 5 shows that the combined effect size of all the hypothesized paths of the TAM model was significant. Thus, hypotheses $H_{TAM}1$ to $H_{TAM}5$ were supported. Secondly, we tested the basic UTAUT model using its fundamental constructs, i.e., the four independent variables – performance expectancy, effort expectancy, facilitating condition, social influence, and the dependent variable behavioral intention. Table 5 also shows that the combined effect size of all the hypothesized paths of the UTAUT model was significant. Hypotheses $H_{UTAUT}1$ to $H_{UTAUT}4$ were supported. Finally, for the integrated conceptual model, all the hypotheses were found to be significant except $H_{ICM}11$ and $H_{ICM}12$. Relationships perceived privacy risk → behavioral intention and price value → behavioral intention were not statistically significant.

Cohen (1988) defined effect size of 0.2, 0.5, and 0.8 as small, medium, and large impact. All the TAM and UTAUT relationships exhibited a moderate to high effect size. This depicts the significance of TAM and UTAUT models in understanding the adoption of wearable devices. Traditional technology adoption theories play a major role in the adoption of wearable devices for health and fitness. Nine out of twelve hypothesized relationships had a high effect size. Variables self-efficacy and price value had a moderate impact on behavioral intention. Perceived privacy risk had a low impact on behavioral intention.

Results of the heterogeneity tests indicated very high levels of heterogeneity for all the three models investigated in this study. $I^2$ value of more than 90% for all the relationships confirmed the high heterogeneity across the relationships. Heterogeneity results favored the selection of a random-effects model over the fixed-effects model for the present study.

## 4.3 Publication bias

Publication bias, also known as the file drawer problem, is the significant threat to the meta-analytic investigations that can affect the validity of the study findings (Egger et al., 1997). The presence of publication bias leads to overrepresentation of literature with positive results (Rothstein, Sutton, & Borenstein, 2006). This paper used Egger's regression model to examine the presence of publication bias. When the p-value is less than 0.05, publication bias is confirmed. Results shown in Table 5 confirmed the presence of publication bias for three of the hypothesized relationships ($H_{UTAUT}2$, $H_{ICM}5$, and $H_{ICM}12$). The proposed conceptual model is revised based on the results of the publication bias.

The relationship between effort expectancy and behavioral intention in the UTAUT model ($H_{UTAUT}2$) and the perceived ease of use and behavioral intention (HICM5) in the integrated model suffered from publication bias. Hypotheses $H_{UTAUT}2$ and $H_{ICM}5$ had an impact size of more than 0.5, and their correlation coefficient had a narrow range. Our results also revealed the publication bias for the relationship between price value and behavioral intention ($H_{ICM}12$). For the hypothesis ($H_{ICM}12$), six out of nine relationships were found to be non-significant. Further, all the non-significant relationships reported negligible correlation values (Park et al., 2016; Sergueeva & Shaw, 2017). However, significant studies have reported very high positive correlations (Talukder et al., 2019; Patton, 2018), which could be attributed to publication bias. The revised conceptual model is shown in Figure 3. Relationships with publication bias were considered as non-significant and represented in dotted lines; Significant relationships were depicted in solid lines.

**Table 5. Meta-analytic results of pairwise relationships**

| Relationship | r mean | $r_+$ | $r_z$ | Combined effect size | Confidence interval | | Heterogeneity | | Publication bias | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | Q- Value | $I^2$ | Egger's regression (t-value) | p-value |
| **TAM Model** | | | | | | | | | | |
| PU – ATT ($H_{TAM}1$) | 0.616 | 0.634 | 0.652 | 0.643*** | 0.564 | 0.710 | 314.781*** | 95.23% | 0.176 | 0.431 |
| PU – BI ($H_{TAM}2$) | 0.593 | 0.572 | 0.586 | 0.614*** | 0.564 | 0.660 | 306.922*** | 91.53% | 1.16 | 0.133 |
| PEOU – PU ($H_{TAM}3$) | 0.539 | 0.506 | 0.527 | 0.554*** | 0.473 | 0.626 | 432.376*** | 95.14% | 0.615 | 0.273 |
| PEOU – ATT ($H_{TAM}4$) | 0.527 | 0.474 | 0.533 | 0.569*** | 0.394 | 0.704 | 869.337*** | 98.39% | 0.535 | 0.301 |
| ATT – BI ($H_{TAM}5$) | 0.609 | 0.574 | 0.591 | 0.627*** | 0.560 | 0.687 | 298.779*** | 93.64% | 1.39 | 0.091 |
| **UTAUT Model** | | | | | | | | | | |
| PE – BI ($H_{UTAUT}1$) | 0.598 | 0.631 | 0.656 | 0.628*** | 0.544 | 0.700 | 305.268*** | 94.43% | 0.858 | 0.202 |
| EE – BI ($H_{UTAUT}2$) | 0.481 | 0.532 | 0.556 | 0.511*** | 0.407 | 0.602 | 240.631*** | 93.77% | 1.405 | 0.046 |
| FC – BI ($H_{UTAUT}3$) | 0.479 | 0.538 | 0.567 | 0.513*** | 0.397 | 0.614 | 292.175*** | 94.87% | 0.783 | 0.223 |
| SI – BI ($H_{UTAUT}4$) | 0.492 | 0.520 | 0.556 | 0.528*** | 0.415 | 0.625 | 438.026*** | 95.66% | 0.641 | 0.265 |
| **Integrated Model** | | | | | | | | | | |
| PU – ATT ($H_{ICM}1$) | 0.616 | 0.634 | 0.653 | 0.643*** | 0.564 | 0.710 | 314.781*** | 95.23% | 0.177 | 0.431 |
| PU – BI ($H_{ICM}2$) | 0.591 | 0.590 | 0.609 | 0.617*** | 0.572 | 0.659 | 663.843*** | 93.37% | 0.789 | 0.217 |
| PEOU – PU ($H_{ICM}3$) | 0.563 | 0.523 | 0.548 | 0.582*** | 0.504 | 0.651 | 498.026*** | 95.38% | 0.979 | 0.169 |
| PEOU – ATT ($H_{ICM}4$) | 0.525 | 0.469 | 0.531 | 0.569*** | 0.380 | 0.713 | 868.923*** | 98.50% | 0.509 | 0.309 |
| PEOU – BI ($H_{ICM}5$) | 0.500 | 0.539 | 0.563 | 0.529*** | 0.453 | 0.598 | 429.940*** | 93.95% | 1.805 | 0.042 |
| ATT – BI ($H_{ICM}6$) | 0.609 | 0.574 | 0.591 | 0.627*** | 0.560 | 0.687 | 298.779*** | 93.64% | 1.39 | 0.091 |
| SI – BI ($H_{ICM}7$) | 0.492 | 0.527 | 0.561 | 0.526*** | 0.425 | 0.614 | 518.471*** | 95.76% | 0.685 | 0.25 |
| INN – BI ($H_{ICM}8$) | 0.551 | 0.531 | 0.762 | 0.575*** | 0.435 | 0.688 | 112.894*** | 94.69% | 0.687 | 0.261 |
| COM – BI ($H_{ICM}9$) | 0.507 | 0.564 | 0.762 | 0.531** | 0.293 | 0.707 | 51.977*** | 94.23% | 2.097 | 0.085 |
| SEF – BI ($H_{ICM}10$) | 0.443 | 0.502 | 0.533 | 0.480*** | 0.370 | 0.576 | 520.728*** | 96.16% | 0.894 | 0.191 |
| PPR – BI ($H_{ICM}11$) | -0.013 | -0.051 | -0.05 | -0.042ns | -0.117 | 0.200 | 259.93*** | 95.00% | 0.991 | 0.171 |
| PV – BI ($H_{ICM}12$) | 0.328 | 0.114 | 0.164 | 0.392ns | 0.049 | 0.652 | 1022.75*** | 99.22% | 2.548 | 0.019 |

*p<0.05, **p<0.01, ***p<0.001

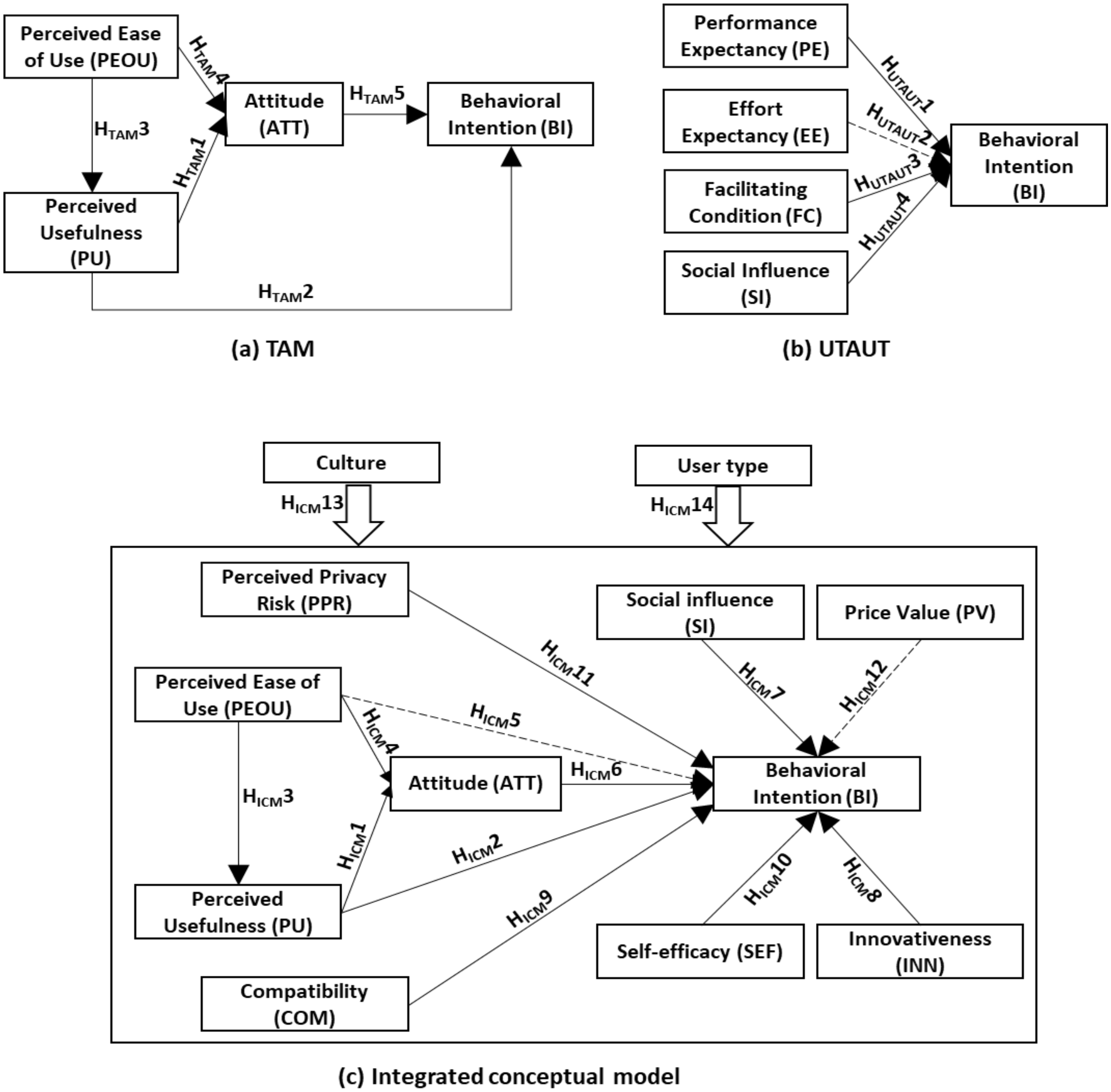


**Figure 3. Revised conceptual model based on Meta-analysis results**

## 4.4 Reliability statistics

Reliability statistic was used to assess the consistency of the measurement model. Cronbach's alpha and composite reliability are the standard measures for determining reliability. We collected the reliability statistics for the integrated model constructs reported in study samples. When Cronbach's alpha was not reported in the study, composite reliability was considered an indicator of reliability. Summary statistics of the reliability values are presented in Table 6. The average reliability values of the ten constructs included in the conceptual model ranged from 0.835 to 0.9. Since the reliability values were above the recommended level of 0.7, these constructs were deemed to be robust enough to be used in the adoption of wearable devices. Reliability analysis established the robustness of the integrated conceptual model.

**Table 6. Reliability statistics**

| Construct | No. of studies | Minimum | Maximum | Average | Variance |
|---|---|---|---|---|---|
| BI | 54 | 0.75 | 0.98 | 0.898 | 0.00 |
| PU | 51 | 0.699 | 0.964 | 0.888 | 0.00 |
| PEOU | 45 | 0.692 | 0.977 | 0.876 | 0.00 |
| SI | 24 | 0.72 | 0.969 | 0.879 | 0.00 |
| SEF | 21 | 0.724 | 0.945 | 0.835 | 0.01 |
| ATT | 17 | 0.647 | 0.96 | 0.862 | 0.01 |
| PPR | 14 | 0.615 | 0.962 | 0.874 | 0.01 |
| INN | 11 | 0.717 | 0.94 | 0.844 | -0.01 |
| PV | 8 | 0.716 | 0.961 | 0.900 | 0.01 |
| COM | 6 | 0.81 | 0.886 | 0.860 | 0.00 |

## 4.5 Moderator analysis - culture

The lurking or exogenous variables could cause high heterogeneity in the relationships. To explain the heterogeneity, meta-analysis was conducted for two possible moderators – Culture and User type. The results of the moderator analysis on culture are summarized in Table 7. Ten out of twelve paths from the integrated conceptual model were examined for the moderating effect of cultural context. The only paths examined by at least two studies in each group were considered for moderator analysis (Zhao et al., 2018). Two pair-wise relationships, compatibility → behavioral intention, and innovativeness → behavioral intention, were not part of the moderator analysis as they did not meet the eligibility criteria. Results showed that the subgroup differences caused by the user type are significant for five paths, i.e., perceived ease of use → perceived usefulness, perceived ease of use → attitude, perceived ease of use → behavioral intention, social influence → behavioral intention, and self-efficacy → behavioral intention. The remaining five paths were not significant. The moderating impact of culture ($H_{ICM}13$) is partially supported.

## 4.6 Moderator analysis - user type

The results of the moderator analysis on user type are summarized in Table 8. Nine out of twelve paths from the integrated conceptual model that satisfied the eligibility criteria were investigated for moderating effect of user type. Three pair-wise relationships, compatibility → behavioral intention, perceived privacy risk → behavioral intention, and price value → behavioral intention, were not part of the moderator analysis as they did not meet the eligibility criteria. Results showed that the subgroup differences caused by the user type were significant for four paths, i.e., perceived usefulness → behavioral intention, social influence → behavioral intention, perceived ease of use → perceived usefulness, and innovativeness → behavioral intention. The remaining five paths were not significant. Thus, the hypothesis $H_{ICM}14$ is partially supported.

**Table 7. Moderator analysis culture**

| Relationship | Group | Number Studies | Combined effect size | 95% CI | Q-value (B\w) | P-value |
|---|---|---|---|---|---|---|
| PEOU-PU | Eastern | 20 | 0.648 | 0.62-0.67 | 21.425 | 0.000 |
| | Western | 4 | 0.515 | 0.48-0.51 | | |
| PEOU-ATT | Eastern | 11 | 0.588 | 0.57-0.62 | 14.772 | 0.000 |
| | Western | 3 | 0.459 | 0.43-0.49 | | |
| PEOU-BI | Eastern | 15 | 0.620 | 0.59-0.65 | 23.087 | 0.000 |
| | Western | 9 | 0.489 | 0.45-0.50 | | |
| PU-ATT | Eastern | 12 | 0.675 | 0.66-0.69 | 5.682 | 0.121 |
| | Western | 4 | 0.662 | 0.65-0.70 | | |
| PU-BI | Eastern | 31 | 0.605 | 0.59-0.62 | 4.713 | 0.130 |
| | Western | 11 | 0.616 | 0.58-0.63 | | |
| ATT-BI | Eastern | 14 | 0.605 | 0.59-0.62 | 7.840 | 0.090 |
| | Western | 4 | 0.578 | 0.55-0.62 | | |
| PPR-BI | Eastern | 6 | -0.057 | -0.08-0.02 | 2.005 | 0.160 |
| | Western | 7 | -0.026 | -0.03-0.08 | | |
| SI-BI | Eastern | 13 | 0.607 | 0.59-0.64 | 13.635 | 0.000 |
| | Western | 7 | 0.451 | 0.39-0.48 | | |
| SEF-BI | Eastern | 11 | 0.477 | 0.43-0.49 | 17.973 | 0.000 |
| | Western | 7 | 0.565 | 0.53-0.58 | | |
| PV-BI | Eastern | 6 | 0.396 | 0.38-0.40 | 1.210 | 0.352 |
| | Western | 3 | 0.389 | 0.35-0.41 | | |

**Table 8. Moderator analysis user type**

| Relationship | Group | Number Studies | Combined effect size | 95% CI | Q-value (B\w) | P-value |
|---|---|---|---|---|---|---|
| PEOU-PU | Non-User | 6 | 0.672 | 0.64-0.72 | 24.590 | 0.000 |
| | Users | 12 | 0.474 | 0.45-0.51 | | |
| PEOU-ATT | Non-User | 3 | 0.480 | 0.33-0.60 | 0.830 | 0.362 |
| | Users | 7 | 0.412 | 0.39-0.44 | | |
| PEOU-BI | Non-User | 3 | 0.564 | 0.51-0.61 | 0.317 | 0.574 |
| | Users | 12 | 0.580 | 0.56-0.6 | | |
| PU-ATT | Non-User | 3 | 0.650 | 0.54-0.74 | 0.021 | 0.886 |
| | Users | 7 | 0.658 | 0.64-0.68 | | |
| PU-BI | Non-User | 7 | 0.631 | 0.59-0.66 | 28.560 | 0.000 |
| | Users | 22 | 0.510 | 0.48-0.55 | | |
| ATT-BI | Non-User | 3 | 0.663 | 0.55-0.75 | 3.271 | 0.071 |
| | Users | 7 | 0.559 | 0.54-0.58 | | |
| SI-BI | Non-User | 2 | 0.304 | 0.20-0.40 | 30.076 | 0.000 |
| | Users | 7 | 0.568 | 0.54-0.60 | | |
| SEF-BI | Non-User | 2 | 0.455 | 0.36-0.54 | 1.630 | 0.202 |
| | Users | 8 | 0.512 | 0.48-0.54 | | |
| INN-BI | Non-User | 2 | 0.342 | 0.26-0.42 | 36.086 | 0.000 |
| | Users | 5 | 0.591 | 0.56-0.62 | | |

# 5 Discussion

This research aimed to investigate the convergence and divergence of the prior studies that had investigated the phenomena: behavior intention to use the wearable devices for health and fitness. This review encompassed 56 empirical studies from 52 articles that examined wearable device acceptance with 16,648 total samples. Findings from the previous studies regarding the relationship between the antecedents and consequences of wearable technology device adoption are mixed. Thus, we performed a series of meta-analyses using TAM, UTAUT, and an integrated conceptual model to provide a comprehensive understanding of the adoption of wearable technologies.

A meta-analysis using the TAM framework confirmed the core TAM relationships. Hypotheses $H_{TAM}1$ and $H_{TAM}2$ were strongly supported. Perceived usefulness emerged as the strongest determinant of attitude (r=0.643) and intention (r=0.614) towards wearable devices. This result is in line with the prior studies (Papa et al., 2020; Park et al., 2016). Hypothesis $H_{TAM}3$ and $H_{TAM}4$ were supported. Results confirmed the perceived ease of use as a significant predictor of perceived usefulness (r=0.554) and attitude (r=0.569). Thus, the reported inconsistencies for the relationship between perceived ease of use and attitude is addressed in our study. The relationship between attitude and behavioral intention ($H_{TAM}5$) was also supported (r=0.627). This result is consistent with that of the prior studies (Sabbir et al., 2020). This indicates that attitude is the critical factor in explaining the adoption of wearable devices. Overall, our result is consistent with the previous meta-analysis studies that synthesized TAM constructs in IS literature (Tao et al., 2020; Schepers & Wetzels, 2007).

Meta-analysis on the UTAUT framework established the significance of all the original UTAUT relationships. Combined effect sizes of performance expectancy, effort expectancy, facilitating condition, and social influence significantly influenced behavior intention. Thus, hypotheses $H_{UTAUT}1$- $H_{UTAUT}4$ were supported. The largest effect size was observed for the relationship between performance expectancy and behavior intention (r=0.628). By reconciling the inconsistencies reported for the relationship between social influence and facilitating condition on behavioral intention, our results confirmed significance of all the UTAUT relationships. All the four fundamental UTAUT relationships were found to be significant in the few studies that investigated the adoption of wearable devices ( Kim & Ho, 2021; Wang et al., 2020). Findings from this study are in line with the previous meta-analytic studies in IS literature based on the UTAUT framework (Khechine, Lakhal, & Ndjambou, 2016; Dwivedi et al., 2011). Despite all the four UTAUT relationships being significant in the meta-analysis, the relationship between the effort expectancy and behavioral intention ($H_{UTAUT}2$) suffered with publication bias. Thus, we have removed this relationship in the revised conceptual model.

A meta-analysis conducted on the basis of TAM and UTAUT frameworks simultaneously, offered several valuable insights on the adoption of wearable devices for health and fitness. Firstly, both the traditional technology acceptance theories (i.e., TAM and UTAUT) were proved to be extremely valuable for understanding the behavior of the individuals to adopt wearable technologies. The technical, usability and social factors ingrained in these theories have played a significant role in exploring wearable technology adoption. Secondly, the analysis provided a comparison of constructs with similar meanings. For instance, perceived usefulness and performance expectancy means the same. Interestingly, 85% of studies investigated the relationship between perceived usefulness and behavioral intention, and 83% of the studies investigated the relationship between performance expectancy and behavioral intention found to be significant. Furthermore, similarities were observed between the coefficient of perceived usefulness → behavioral intention (r=0.614) and the coefficient of performance expectancy → behavioral intention (r=0.628). Perceived usefulness in TAM and performance expectancy in UTAUT had the largest effect sizes. All this confirms that the usefulness of the wearable devices to monitor health and fitness parameters and the ability of the wearable devices to meet the health and fitness goals becomes critical for the diffusion of wearable devices. Finally, despite the similarities in constructs, relationships, and effect sizes, the number of studies investigating the TAM relationships was higher than that of the number of studies investigating the UTAUT relationships. This result reaffirms TAM as a powerful framework to investigate the emerging technology aspects.

The relationships framed in the integrated conceptual model were synthesized using the meta-analysis. Our results supported hypotheses $H_{ICM}1$, $H_{ICM}2$, and $H_{ICM}6$. Relationships perceived usefulness → attitude, attitude → behavioral intention, and perceived usefulness → behavioral intention were found to be significant. Our results indicated perceived usefulness and attitude as strong predictors of behavioral intention. This shows that introducing new device attributes and improving service usefulness to effectively track health and fitness parameters are crucial for wearable device adoption. This result is consistent with the findings of the prior studies (Lin et al., 2016; Park et al., 2016).

Hypotheses $H_{ICM}3$-$H_{ICM}5$ proposed that perceived ease of use is the predictor of perceived usefulness, attitude, and behavioral intention. Prior research on wearable devices have reported conflicting results. In particular, a few studies have reported perceived ease of use as a non-significant predictor of perceived usefulness (Lai & Huang, 2018; Chang et al., 2016), attitude (Vongurai, 2020), and behavioral intention (Blumenthal et al., 2018). We have reconciled the conflicting findings and performed a combined effect size analysis. Our findings supported the hypotheses $H_{ICM}3$, $H_{ICM}4$, and $H_{ICM}5$. However, the relationship between the perceived ease of use and the behavioral intention ($H_{ICM}5$) fail to pass the publication bias test. Our results have established perceived ease of use as an essential dimension for the adoption of wearable devices. This result is in line with the findings from the previous studies (Sabbir et al., 2020; Li et al., 2019).

Hypothesis $H_{ICM}7$ proposed the relationship between social influence and behavioral intention, was supported in our analysis. Even though wearable devices' research was divided on the impact of social influence, our combined effort size analysis revealed social influence as a significant predictor of wearable device adoption. This result was aligned with the previous research findings (Binyamin & Hoque, 2020; Talukder et al., 2020). Thus, designing, deploying, and promoting social forums and social events through the devices to effectively engage social groups were found to be significant for the adoption of wearable devices in society.

Hypotheses $H_{ICM}8$ and $H_{ICM}9$ proposed that innovativeness and compatibility had a significant positive impact on behavioral intention. Our results indicated both innovativeness and compatibility had a positive effect on behavioral intention. These findings are aligned with the prior studies (Talukder et al., 2019; Park et al., 2016). Our findings indicated that individual differences in terms of innovativeness, and compatibility of wearable devices with the lifestyle and other communication devices were significant for adopting wearable technologies.

Hypothesis $H_{ICM}10$ proposed the relationship between self-efficacy and the behavioral intention, and this was supported in our analysis. Prior research on wearable devices indicated divergent perspectives on the significance of self-efficacy on the adoption of wearable devices (Sergueeva & Shaw, 2017). We have reconciled the divergent perspectives in our analysis, and results confirmed that self-efficacy had a positive impact on the adoption of wearable devices. Developers of wearable devices should make concerted efforts to boost users' confidence by making the wearable devices easily accessible.

Hypothesis $H_{ICM}11$ proposed the relationship between perceived privacy risk and behavioral intention. Quite surprisingly, this relationship was not supported in our analysis. This finding is supported in prior studies (Sergueeva et al., 2020; Scott, 2020). Wearable technology devices collect, store and analyze health information regularly. Privacy is an important factor as wearable devices are dealing with health-related information. Lack of awareness about data breaches and privacy-related incidents and that only limited studies have investigated this relationship could be attributed to the non-significant relationship.

Hypothesis $H_{ICM}12$ proposed the relationship between price value and the behavioral intention was not supported. This result is consistent with the findings from the previous studies (Beh et al., 2021; Talukder et al., 2020). Availability of wearable devices at different price points and the value derived from maintaining health and fitness abate the financial outlay involved in purchasing the device (Park et al., 2016). Result of this hypothesis should be interpreted with caution as this relationship exhibited publication bias.

Hypothesis $H_{ICM}13$ proposed the moderating impact of culture on the antecedents of the behavioral intention to use wearable devices. High heterogeneity reported for the relationships investigated in the integrated conceptual model prompted us to explore the moderating effect of culture. Our results indicated that five out of ten relationships confirmed the moderating effect of culture. Thus, hypothesis $H_{ICM}13$ is partially supported. Perceived usefulness had a high effect size on attitude and behavioral intention in both eastern and western cultures. There is consensus across cultures on the usefulness of wearable technologies and their effect on attitude and intention to use wearable devices for health and fitness. Culture had a significant moderating impact on the relationship of perceived ease of use on perceived usefulness, attitude, and behavioral intention. Perceived ease of use significantly differs across eastern and western cultures. Perceived ease of use emerged as a significant factor for the adoption of wearable devices in eastern culture. This finding is consistent with the previous meta-analysis studies (Sarkar et al., 2020; Schepers & Wetzels, 2007).

Culture had a significant moderating impact on the relationship between self-efficacy and behavioral intention. It is surprising to note that self-efficacy had a high impact on western cultures. The considerable rise in mobile devices and other handheld devices in eastern countries has increased the confidence to use wearable devices (Baudier et al., 2020). The nature of the people from collective cultures is to learn in groups; this could also be attributed to the high self-efficacy in eastern cultures. Additionally, in the eastern culture, the diffusion of wearable devices is still in infancy (Beh et al., 2021). Technologies in the early phase are adopted by technology enthusiasts who are mostly youngsters and people familiar with the technology. This could also be the reason for high self-efficacy in eastern culture. Finally, culture moderated the relationship between social influence on behavioral intention. As expected, behavioral intention in eastern culture is significantly affected by social influence. Individuals coming from a collective culture will respect the opinion arising from the reference groups (Srite & Karahanna, 2006). Our result is aligned with the findings from the previous meta-analysis (Zhao et al., 2021).

Hypothesis $H_{ICM}14$ proposed the moderating impact of user type on the antecedents of the behavioral intention to use wearable devices. The user type had a moderating effect on four of the nine relationships examined. Thus, hypothesis $H_{ICM}14$ is partially supported. This result is consistent with the findings from the previous meta-analysis studies (Tao et al., 2020). Through the moderator analysis, this study brought out the dichotomy that exists between the users and non-users. User type had a significant moderating effect on the relationship between perceived ease of use and perceived usefulness. The effect size of this relationship was larger for the non-users and low for the users. It implies that non-users would have apprehensions about the ease of use associated with wearable devices. However, users weigh ease of use lightly because their experience of using multiple features enables them to operate the devices without much effort. The result indicated that user type moderated the relationship between perceived usefulness and behavioral intention. The effect size of this relationship is larger for the non-user groups. This implies that non-users or potential users would typically be excited about the innovative features ingrained in the wearable devices. Our result indicated that user type moderated the relationship between innovativeness and behavioral intention. The impact of innovativeness on behavioral intention to use wearable devices tended to be higher among the users. Results showed that user type moderated the relationship between social influence and behavioral intention. Results indicate that social factors are motivating users to adopt wearable devices. This implies that social forums, networking capabilities, and health events organized through wearable devices act as driving forces for the user’s adoption of wearable devices (Talukder et al., 2020; Binyamin & Hoque, 2020).

## 5.1 Theoretical implications

By collating, reviewing, and synthesizing rapidly evolving research, we seek to instill clarity on the inconsistent findings and deepen the understanding of the adoption of wearable devices for health and fitness.

First, we synthesized the dominant theoretical frameworks (i.e., TAM and UTAUT) applied in the context of wearable devices. Our meta-analytic findings revealed strong support for these frameworks in explaining the antecedents of behavioral intention to use wearable technology devices. The meta-analysis established the consistency and robustness of the TAM constructs on an individual’s decision to adopt wearable devices for health and fitness. Most of the previous meta-analysis studies had synthesized the original and extended version of TAM constructs (Zhao et al., 2018; Tao et al., 2020) or UTAUT constructs (Khechine et al., 2016). This study is a pioneering effort to conduct meta-analysis using both TAM and UTAUT models to investigate the adoption of wearable devices, facilitating simultaneous discussion and comparison between these two dominant models in technology adoption. The findings from this study will motivate the IS/IT scholars to carry out meta-analyses using multiple theoretical lenses to bring consolidated perspective through meta-analysis.

Second, we developed an integrated conceptual model of wearable device adoption based on the theoretical relationships drawn from the literature. The conceptual model was successfully tested using the meta-analytical framework. Our results confirmed perceived usefulness, attitude, social influence, innovativeness, and self-efficacy as significant predictors of behavioral intention to use wearable devices. Non-significant results were obtained for the impact of perceived privacy risk and price value on behavioral intention. Impact of perceived ease of use, social influence, price value, and perceived privacy risk on behavioral intention exhibited inconsistent findings in the literature. Thus, the meta-analytic findings infuse generalizability to the relationships where discrepancy existed. Our findings can guide the scholars to make informed decisions on choosing the variables to investigate the acceptance of wearable devices.

Third, this study contributes to the theory by unraveling the moderating impact of culture and user type. Both moderators were partially supported in our analysis. Results confirmed the moderating role of culture on perceived ease of use, social influence, and self-efficacy on behavioral intention. Perceived ease of use had a high impact on eastern culture and moderating impact on western culture. Western countries are technologically advanced economies wherein individuals have better exposure to advanced technologies compared to eastern countries (Sarkar et al., 2020). This augments the low importance that westerners attribute to perceived ease of use. Social influence emerged as the key driver of intention to use wearable devices in eastern culture, delineating the nature of collectivism (Zhao et al., 2021). Increasing penetration of information and communication technologies in eastern culture could be the reason for the increased self-efficacy in eastern culture. User type moderated the impact of perceived usefulness, perceived ease of use, social influence, and innovativeness. Non-users exerted a strong influence on the explicit factors such as usefulness and ease of use. In contrast, implicit factors such as social activities promoted through wearable devices and innovative features in the wearable devices seem to drive the adoption of wearable devices among the users.

Several of the critical factors towards wearable device adoption have been overlooked in the literature. Wearable devices increasingly find their application and use in healthcare contexts. Wearable devices are useful in tracking the health condition of the elderly and people with chronic conditions (Beh et al., 2021). However, the impact of health attributes in affecting intention to use wearable devices is currently lacking. Privacy risk becomes extremely important for wearable devices as they constantly collect bio signals and health information about the wearers of the device. Yet, the privacy risk is overlooked in the research on the adoption of wearable technologies. Through our review, we didn’t encounter non-user-based studies investigating the privacy perspective. It would be interesting for future studies to investigate the differences in the privacy risk considerations among users and non-users. The USP of wearable devices is to promote positive lifestyle changes in consumers. But the compatibility of wearable devices among individuals and their impact on the adoption is overlooked in the literature.

## 5.2 Practice implications

Collating findings from numerous studies and drawing new evidence from the meta-analysis provides several useful insights for the practitioners. Perceived usefulness is unequivocally established as an important determinant of wearable technology adoption. Wearable devices cater to a wide range of users, i.e., professional runners, fitness enthusiasts, patients with chronic conditions, and anyone who wishes to monitor their health and fitness. Wearable devices in the market cater to basic monitoring of steps and distance to advanced sleep analytics, ECG, fall detection, oxygen saturation, etc. Marketers should continuously innovate and introduce newer monitoring capabilities that can meet diverse user needs. By consolidating health data generated by different sensors, future wearable devices can create a health profile of the wearers and integrate with the healthcare providers and insurance agencies (Sabbir et al., 2020). Additional services for health promotion can create a positive attitude towards wearable devices. Our moderator analysis showed a low impact of perceived usefulness for users. Practitioners can roll out novel features for the users through software upgrades.

Perceived ease of use and self-efficacy were also found to be significant. Practitioners should also make concerted efforts to develop user-friendly platforms that can enhance confidence among users to utilize the devices to the fullest extent. Developers can leverage design principles to build a simple watch interface, intuitive mobile interface; they can also introduce tutorials and videos to promote wearable technologies (Baudier et al., 2020). Cultural aspects should be given importance in the usage of languages in apps and manuals.

Compatibility is another crucial dimension for the success of smartwatches. Wearable devices should not only be compatible with the consumer’s lifestyle; they must be compatible with smartphones and other handheld devices. This requirement slightly changes with respect to the type of wearable devices. In the case of smartwatches, users can visualize the monitoring data with the help of mobile apps installed on the device. Whereas in the case of fitness bands, users can only view the data in smartphone apps. Thus, compatibility is vital for fitness bands (Talukder et al., 2019).

Social influence is the significant antecedent of behavioral intention. Hence, the managers' efforts should make the wearables appealing to the society as a whole, not just to some individuals (Talukder et al., 2020). Our moderator analysis underscored the importance of social influence in eastern culture. Thus, managers should devise more social engagement initiatives for eastern cultures. Non-users tend to weigh less importance on social influence. Marketers should conduct awareness programs on social activities, particularly for potential users (non-users).

Non-significant results were obtained for perceived privacy risk on behavioral intention. Results imply that privacy is not a factor impeding the adoption of wearable devices (Scott, 2020). Given the scope of wearable devices expanding to the realm of healthcare, privacy should be given critical importance. Policymakers should develop regulations to cover the collection, storage, and usage of personal health information. Consumers should be empowered to retain complete control over the data. Developers can achieve this by implementing transparency in data collection and use (Li et al., 2016).

Innovativeness does have a significant impact on the adoption of wearable devices. A large proportion of the sample in many studies were young individuals (Beh et al., 2021). It shows the awareness and penetration of wearable devices among the young population who possess high innovativeness. As wearable technology will likely move from people with high innovativeness to low innovativeness, the managers must switch gears to pay increased attention to dimensions such as ease of use and self-efficacy.

### 5.3 Limitations and future research

There are some limitations to the meta-analysis conducted in this study. First, despite the meticulous search strategy employed in the study to retrieve articles from the relevant databases, articles that were not available in these databases were not included in our analysis. The second limitation is with respect to the inclusion criteria. Relationships reported in at least three studies were considered in the analysis. Other meaningful relationships examined in fewer studies were not part of this analysis. As newer constructs and relationships evolve, future meta-analytic studies may accommodate these relationships. Third, the results of the current meta-analysis are univariate statistics, computed mainly using correlation coefficients of the relationships. Future studies can consider using multivariate techniques such as structural equation modeling or meta-regression for the analysis. Fourth, this study considered the moderator's user type and culture. The user age group is the potential moderator for the adoption of wearable devices. However, this study did not consider the user age group because few studies have considered the different age groups.

One of the ways to combat the publication bias is to expand the search strategy to include published and unpublished studies, including dissertations. Despite expansive search criteria, three relationships in this study suffered from publication bias. Firstly, caution should be exercised in interpreting these results. Further, future meta-analytic investigations can consider the following strategies to combat publication bias: (i) inclusion of working papers, (ii) inclusion of articles published in a language other than English, and (iii) finally, if the studies have not reported the sample size or the correlation coefficients, corresponding authors may be contacted to obtain the required information. Future research can perform systematic literature reviews driven by this study finding to gain a deeper understanding of the implications for specific streams of wearable devices, i.e., smartwatches, fitness trackers, smart garments. Future research on the adoption of wearable health devices can consider adopting health attributes (i.e., health information sensitivity, health information accuracy), privacy, and compatibility. It would also be interesting for future research to investigate the differential impact of privacy on the potential users and actual users. Moreover, primary empirical investigations simultaneously examining the adoption of wearable devices in multiple cultural contexts (eastern vs. western) are currently lacking in the literature. Future studies can fill this gap. We also recommend future studies to update the meta-analytic findings with the potential moderators such as user age group, gender, and wearable device type. Future research can also compare how different the results will be when wearable technology is adopted for health and non-health (i.e., fashion accessory, e-commerce) purposes.

## 6 Conclusion

This research quantitatively synthesized studies conducted on the adoption of wearable technology devices for health and fitness using meta-analysis. Our results show that constructs from TAM and UTAUT models are preferred by scholars to investigate the factors influencing the adoption of wearable technology. This study also made an attempt to compare the impacts of TAM and UTAUT constructs by investigating the intention to use wearable devices. We also identified several antecedents and consequences beyond the traditional technology acceptance theories through the integrated conceptual model. The results established the moderating effects of cultural differences and user type in understanding the behavioral intention to use wearable devices. Our findings would help researchers and managers in understanding and incorporating the features that will lead to the widespread adoption and use of wearable devices for health and fitness.


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