A Task-Technology-Identity Fit Model of Smartwatch Utilisation and User Satisfaction: A Hybrid SEM-Neural Network Approach

Mazen El-Masri[1] · Karim Al-Yafi[1] · Muhammad Mustafa Kamal[2]

Abstract

Smartwatches are wearable devices intended to be smartphone companions that capture health data and ease access to notifications. They have also become personalisable standing as a fashion statement. This combination resulted in staggering adoption rates recently leading to question whether smartwatch users' choice and use satisfaction emerge from utility features or from its fashion characteristics. This paper proposes and validates a fit theory to investigate the antecedents of adopters' satisfaction. Besides evaluating fit with identity, the model assesses both perceived and actual task-technology fit of smartwatches. A questionnaire-based quantitative approach is used to collect data from about 300 smartwatch users in Qatar. To test the proposed model, data is analysed using structural equation modeling (SEM) and artificial neural networks (ANN). Furthermore, ANN sensitivity analysis ranks the importance of the fit factors affecting users' choice during pre- and post-adoption stages. Both task-technology and technology-identity fit factors are quasi-equally important in explaining 62% of satisfaction variance. ANN analysis revealed that post-adoption satisfaction is primarily attributed to smartwatches' ability to fit with users' identity and secondarily to its perceived fit with tasks. Nevertheless, pre-adoption choice of smartwatches is mainly guided by their functionality. This paper is the first to propose and validate an integrated task-technology-identity fit model to explain smartwatch utilization and users' satisfaction. The originality also lies in assessing actual task-technology fit and as perceived by users. Employing two modes of analysis revealed extra insights too.

Keywords Smartwatch · Task-Technology Fit · Technology-identity fit · Utilisation · Satisfaction

1 Introduction

According to Allied Market Research[1], the smartwatch market exceeded 20 billion dollars in 2019 and is expected to climb to around a 100 billion dollars in 2027. With such value

attributed to this wearable device, the research community has placed in recent years immense efforts to investigate its different aspects like its hardware, marketing methods, and utility (Iftikhar et al., 2020; Kim & Shin, 2015). Yet, a closer look at the nature of research that has been published[2] on wearable devices reveals that the majority of publications fall under computing and electrical engineering related sub disciplines. Only 16% of published research is related to information systems (IS); of which a good number of articles examine the wearables only as a health tracking assistant (e.g. see Piccialli et al., 2021; Ghahramani & Wang, 2019). Regardless of the number of the published articles, the main aim of this reseach is that user's satisfaction with the smart devices they utilise can be better comprehended if we evaluate how this smarwatch technology fits with their utilitarian and identity needs. Smartwatches as wearable devices have been used to capture health data, ease access

---

[1] https://www.alliedmarketresearch.com/smartwatch-market.

✉ Muhammad Mustafa Kamal
muhammad.kamal@coventry.ac.uk

✉ Mazen El-Masri
mazen.elmasri@qu.edu.qa

✉ Karim Al-Yafi
karim.alyafi@qu.edu.qa

[1] College of Business and Economics, Qatar University, Doha, Qatar

[2] School of Strategy & Leadership, Coventry Business School, Coventry University, Coventry, UK

---

[2] Indexed in SCOPUS.

to Apps notifications, communicating with friends trachting workouts, including tagged as a fashion product (Krey, 2019). The increasing adoption rates led to highlight the research gap as well as question whether smartwatch users' choice and use satisfaction emerge from utility features or from its fashion characteristics.

Smartwatches are "embedded portable computers and advanced electronics that integrate seamlessly into people's daily lives and enable them to interact with a smart environment" (Dehghani et al., 2018). Users can download and utilises apps that can help them perform many of their routine tasks (Chuah et al., 2016; Curry, 2015). Those smartwatches are equipped with a multitude of sensors coupled with internet and Bluetooth connections to become smartphone companions to do messaging, e-mailing, placing and receiving phone calls, social media notifications, and entertainment (Dehghani et al., 2018; Jeong et al., 2017; Xia et al., 2014). The extant literature also informs the exponential growth of mobile telephony including to 4 to 5G networks, resulting in customers connected with smart devices e.g. smartwatches, Siri, Alexa, etc., spawning huge digital traces for service providers (Muhammad et al., 2018).

Predominantly, the relevant IS literature on smartwatches examine the factors that contribute to intentions to purchase (Hsiao & Chen, 2018; Wu et al., 2016), adoption (Adapa et al., 2018; Chuah et al., 2016; Dehghani, 2016; Dutot et al., 2019; Krey et al., 2019), use (Choi & Kim, 2016; Clermont et al., 2020; Mettler & Wulf, 2019), continuous intentions to use Bölen, 2020; Dehghani, 2018; Hong et al., 2017), and use discontinuance (Nascimento et al., 2018; Wairimu & Sun, 2018; Xiao-Liang et al., 2018). Nevertheless, to better understand where the smartwatch innovation is headed can be remarked in the few articles that question users' intentions to continue or discontinue to use a smartwatch. Indeed, some of the recent literature have questioned the usability of such wearables while others observed a significant drop of use after a period of time (Lazar et al., 2015). This branch of research argues that this wearable technology is witnessing an identity crisis (Nieroda et al., 2018) and question whether they are the appropriate technology to fit the intended tasks (Wairimu & Sun, 2018) and if the smartwatch hype will last (Dehghani et al., 2018).

Simultaneously, IS and fashion research began perceiving such wearable technologies as fashion products (Choi & Kim, 2016; Iftikhar et al., 2020). Indeed, recent smartwatch releases include new technological components and functionalities along with new ways to customise and accessorise the technology. They are also becoming more customisable and stylish (Chuah et al., 2016; Kim & Park, 2019). Accordingly, IS researchers remarked the importance of people's psychological needs to express themselves with luxury fashion produces (Choi & Kim, 2016; Jung et al.,

2016). While some users find it practical for emails and call notifications (Jeong et al., 2017) and social media (Adapa et al., 2018) others just want to be noticed (Chuah et al., 2016). Some people indeed are fashion addicts and just like being stylish (Nieroda et al., 2018).

Accordingly, the main question that we ask is not whether "a smartwatch is an IT product or a fashion product" (Choi & Kim, 2016) because the literature clearly shows that it is both. Moreover, the extant empirical research is also clear that factors that affect people's intention to purchase, adopt, use, and continue to use smartwatches are related to the features of the technology, the individuals' characteristics, the tasks that people use the technology. This area has been examined rather extensively. However, it seems more cogent to understand how this technology not only fits with what people need to accomplish in certain tasks, but also how it fits in peoples' lifestyle, as a fashion statement while being a utility too. The latter argument is supported by Filieri et al., (2017), who report that smart devices have become a core part of many consumers' lifestyles to perform various social, cogntive and business activities.

To this end, this paper builds on the extant research that examines how individual characteristics, whether related to identity, psychological needs, or practical needs relates to people's use and satisfaction with their smartwatch. We examine user's satisfaction and use of the technology during the post adoption period of the life of the technology. Our premise is that people can still be satisfied with their smartwatch even if they underutilise it simply because it aligns with their psychological needs. Therefore, the theoretical framework that governs our investigation is fit theory instead of the behavioural and attitudinal theoretical lenses predominantly adopted in research. We judge that consumer technologies such as wearables afford non-utilitarian values that must be taken into consideration. Indeed, wearables are more distinctive than technological devices like laptops and smartphones and such technologies must fit the identity of the beholder. A number studies presented in this paper add to the evidence that in an increasingly multifaceted and interrelated world where communities are combating with COVID-19 pandemic and social distancing is observed worldwide, consumers may benefits more from a breadth of means in which to interact and communicate, so they have the ability to choose the best technology to fit (suit) their needs (Wang et al., 2021; Brodsky, 2021). Stemming from these logics, we conceptualise and specify a new fit construct, technology-identity-fit, to gauge the degree of alignment between what the technology offers, and the beholder's personality and identity needs and we expand Goodhue's (1998) TTF model to incorporate this construct. The main research question that this paper seeks to answer is *whether users' satisfaction with their smartwatch solely the result*

of their sensible utilisation of the technology or must such wearable devices fit with the users' identity as well.

The rest of the paper is organised as follows. In the next section, we will describe the existing literature on the topic. Since there has been recent publications that exhaustively review the relevant literature, this section will be concise. The following section will explain the proposed model and the concepts it incorporates. Afterwards, we will describe the methodology adopted to validate the model, provide the results of our data analysis. Towards the end of the paper, we will discuss our results and implications, list the limitations, and offer concluding remarks.

2 Literature Review

The extant research on wearables, and more specifically smartwatches, focuses on the technological specifications and advancement (e.g. Zadeh et al., 2020). Web of Science and SCOPUS databases classifies around 85% of the literature under computer science, engineering, telecommunications, and cyber security. A comprehensive review of the smartwatch literature that can be classified under the technology-focused theme can be found here (Niknejad et al., 2020). In information systems, research has mostly treated the technology as a black box and the main emphasis was placed on factors that lead to preadoption perceptions and postadoption behaviour. A closer review of this literature reveals a number of theoretical frameworks under which users' intentions to adopt, use, and continuous use phenomena are examined. Yet, a good majority of this research can be classified under theories of behaviour and attitude; and more specifically ones derived from Fishbein and Ajzen's (1975) theory of reasoned action.

Some of the most utilised theoretical models to examine smartwatch user behaviour are the Technology Acceptance Model (TAM) (Choi & Kim, 2016; Chuah et al., 2016; Dutot et al., 2019; Kim & Shin, 2015; Nasir & Yurder, 2015; Niknejad et al., 2020), Unified Theory of Acceptance and Use of Technology (UTAUT) (Dehghani, 2016; Gu et al., 2016; Rubin & Ophoff, 2018), Expectation Conformation Theory (Bölen, 2020; Ernst & Ernst, 2016; Pal et al., 2018), and Innovation Diffusion Theory (Dehghani, 2018; Hong et al., 2017). A comprehensive literature review by Niknejad et al., (2020) shows that, unequivocally, TAM is the adoption model of choice to examine user behaviour with 25 articles, followed by DOI (diffusion of Innovation) and UTAUT with 12 and 11 articles respectively. Moreover, many researchers found value in combining concepts from different theories to better understand smartwatch user behaviour and use (Gao et al., 2015; Wu et al., 2016).

The aforementioned research provided useful insights on the factors that led people to adopt, use, continue to use, or stop wearing a smartwatch. Indeed, the adapted theoretical models on user behaviour such as TAM, UTAUT, and DOI point at the usual factors such as perceived ease of use, perceived usefulness, social influence, effort expectancy, perceived complexity, perceived control, etc. as antecedents of adoption, use, and post-use behaviours. Perhaps more importantly, a few recent investigations emphasized the relevance of the smartwatches' non-utilitarian features in predicting user adoption and use or lack thereof and incorporated them in their behavioural models. Some of the main factors that deemed to influence on user behaviour vis-à-vis smartwatch include the smartwatch hedonic and fashionable features (Dehghani et al., 2018; Iftikhar et al., 2020), design aesthetics (Bölen, 2020; Dehghani & Kim, 2019; Hsiao & Chen, 2018; Jung et al., 2016; Nieroda et al., 2018), uniqueness (Choi & Kim, 2016; Dehghani & Kim, 2019), and vanity and expressiveness (Choi & Kim, 2016; Hsiao & Chen, 2018).

Notwithstanding the value of those theories in examining technology adoption and use, they do not provide knowledge on how this technology fits in the life of the adopter. Smartwatches are observed in research as auxiliary technologies. To remain in use, they must compete with primary technologies that people use such as smartphones and personal computers. Accordingly, such wearables must fit well with the tasks that adopters perform. Moreover, given the perceived characterisation of smartwatches as a fashion statement, smartwatches must also fit with the personality and style of the adopter. One theoretical model that gauge the degree of fitness between the technology and what is expected from it is the task-technology-fit model (Goodhue, 1998; Goodhue & Thompson, 1995). Fit is a theory of aligning "tasks, systems, individual characteristics, and performance" (Goodhue, 1998). This theoretical lens posits that utilisation occurs only when technology fits the intended tasks (Howard & Rose, 2019). TTF has been used to examine the alignment of various technologies with their intended tasks including social network sites (Bravo & Bayona, 2020; Lu & Yang, 2014), decision support systems (Erskine et al., 2019), smart-glasses (Klinker et al., 2018), MOOCs (Larsen et al., 2009; Wu & Chen, 2017), smartphones (Joo & Sang, 2013), and social media (Al-Maatouk et al., 2020).

Nevertheless, the application of TTF theory has been criticized. For instance,

- First, the *conceptualisation of TTF*, and subsequent *operationalisation*, has often been confounded with utilisation; a concept it is expected to predict (Howard

& Rose, 2019; Lee & Lehto, 2013; Pagani, 2006; Strong et al., 2006).

- Second, the key *motivation to adopt TTF theory* is that it focuses on utilisation as a dependent variable. Some information systems research adopts TTF to examine intentions to use rather than utilisation (Cane & McCarthy, 2009). Yet, intentions to use might not lead to actual use (Cane & McCarthy, 2009; Dishaw & Strong, 1998).
- Third, the concept of fit in IS research has been conceptualised either as a *moderator* (i.e. derived interaction relationship between two variables that predicts the third), *matching between two related variable*, or as *self-reported deviation from profile* (Dishaw & Strong, 1998; Howard & Rose, 2019; Venkatraman, 1989). For instance, Bravo & Bayona (2020); Erskine et al., (2019); and Wu & Chen (2017) conceptualised the TTF construct as self-reported deviation, denoting the degree of (mis)fit between the technology and users' tasks. Conversely, other research measured actual fit by matching the technology characteristics with the task characteristics (see Lu & Yang 2014).

According to Cane & McCarthy (2009), the great majority of researchers adopt one of these approaches. However, the matching or moderator approach could be problematic as the list of all possible tasks and technology characteristics of a certain technology might not be easy to determine (Howard & Rose, 2019). This is particularly true for modern multipurpose technological gadgets such as smartphones and smartwatches. Overall evaluations of users' utilisation and satisfaction with such devices may not be accurate due to attitudinal ambivalence, which occurs when contradicting beliefs coexist in users' evaluation of a system (Olsen et al., 2005; Shen et al., 2018). Therefore, estimating individual features, or feature groups belonging to a specific use case, rather than the whole system, may present a more accurate estimation of utilisation rate and satisfaction level.

After reviewing how TTF is conceptualised in IS research, Howard & Rose (2019) recognised that most researchers find self-reported, or *perceived*, TTF (i.e. profile deviation) predicts utilisation better than deriving *actual* TTF as is the case with matching or moderator approach. Yet, it is important to incorporate the two approaches to evaluate the entire TTF theory framework. *Perceived* TTF estimates fit holistically while *actual* TTF provides dimensional estimation specific to the technology and tasks under study and suggests that future research should merge those two approaches (ibid.).

Pertaining to the non-utilitarian technology characteristics that lead to adopting a fashionable technology such as a smartwatch, it is equally important that they match the identity of the adopter. Wearables are more distinctive than other technologies and must fit the identity of the beholder. While the literature provides insights on those fashion-related characteristics (see Dehghani et al., 2018; Dehghani & Kim, 2019; Choi & Kim, 2016; Iftikhar et al., 2020), they might not necessarily fit the identity of all adopters. Previous attempts to conceptualise the fit between the individual and the technology can be found in the IS literature. For instance, Wu & Chen (2017) developed a self-reported individual-technology fit construct to measure whether the MOOCs used by students match their learning styles. Alternatively, Yu & Yu (2010) defined a similar learner-technology fit but matched the individual characteristics with those of the technology.

To the best of authors' knowledge, only one study (see Hsiao 2017) examined smartwatch adoption using TTF theory. However, their objective was to evaluate the effect of the degree of fit between task and technology as it relates to user's intentions to adopt and not utilisation. Proponents of TTF theory suggests otherwise (Cane & McCarthy, 2009; Dishaw & Strong, 1998). Moreover, their operationalisation of the TTF seems to confound with utilisation as it measures whether smartwatch functionalities are useful, appropriate, or adequate. This confoundment was highlighted in a recent review by Howard & Rose (2019) who suggests that TTF must only focus on the match between the technology and users' tasks. Stemming from this recommendation and potential research gap, future research studies also need to focus on examining the link between smartwatch adoption using TTF theory in more detail including diffusion, acceptance and utilisation of wearable technologies, on not merely linking such smart devices with fashion but its usefulness to consumers on a wider scale.

3 Theoretical Model

The model suggested below is the result of a thorough review of the literature on the adoption, use, and continuous to use or lack thereof of technologies and more specifically smartwatches (e.g. Chuah et al., 2016; Fillieri et al., 2017; Dehghani et al., 2018; Mettler & Wulf, 2019; Bölen, 2020; Al-Emran, 2021). Our main premise is consistent with prominent IS research that advocates TTF theory to measure utilisation (e.g. see Venkatraman 1989, Cane & McCarthy, 2009; Dishaw & Strong, 1998; Howard & Rose, 2019; Dang et al., 2020). The smartwatch technology have moved to a post adoption phase and the recent research suggests discontinuity of smartwatch use (Lazar et al., 2015) as they might not be appropriate for users' tasks (Wairimu & Sun, 2018). In line with the former (i.e. Lazar et al., 2015), consumers stopped using smart devices for reasons such as devices either did not fit with participants' conceptions

of themselves, collected data not being useful, or devices requiring too much work and maintenance, whereas, according to the latter (i.e. Wairimu & Sun 2018), smartwatches are changing consumer experience in two aspects of utility and hedonism. In doing so, they (ibid.) proposed a framework for distinguishing consumers satisfaction based on confirmation/disconfirmation of expectations they have on the smartwatches. To put adoption rates in perceptive, in the first quarter of 2020, 13.7 million Apple smartwatches were sold (Brown, 2020). It seems that a more crucial question to examine is how this technology fits in adopters' life whether as a technology to accomplish their routine tasks or as a fashion statement and how this fit affects utilisation and subsequent satisfaction.

As shown in Fig. 1, this paper adopts a theoretical model consistent with Howard & Rose (2019) who posit that TTF is the match between a task and a technology. It is not the properties of tasks or technologies, but it arises from their combination. However, this research conceptualises two fit constructs instead of one i.e. (1) task-technology-fit (i.e. IT is more likely to have a positive impact on individual performance), and (2) identity-technology-fit (i.e. measuring the degree of alignment between what the technology offers, and the beholder's personality and identity needs). In the former context, task-technology-fit signifies the level to which a specific technology (i.e. smartwatches) facilitates a consumer's effort to perform a given task with the smart device (Al-Maatouk et al., 2020), whereas in the latter context, we attend to the suggestions of Howard & Rose (2019) that, in order to gauge task-technology-fit more accurately, both perceived TTF (which is the deviation from ideal profile) as well as actual TTF (matching the task and the technology characteristics) is preferred. Accordingly, our model incorporates the two TTFs constructs; perceived and actual. We expect that both perceived and actual TTF will lead to utilisation; which subsequently results in a satisfied user. Consequently, we propose the first two hypotheses as follows:

H1 *Task Technology Fit (TTF) positively influence the utilisation of the smartwatch.*

H2 *TTF is a formative construct composed of both Perceived TTF and Actual TTF.*

Accordingly, H2 can be decomposed into two sub-hypotheses:

H2a *Perceived TTF is a significant component of TTF.*

H2b *Actual TTF is a significant component of TTF.*

TTF theory suggests that the utilisation construct as a moderator of the relationship between TTF and other performance outcomes (Heine et al., 2003; Teo & Men, 2008). Indeed, previous research that examine the relationship between TTF and utilisation also expect that utilisation will lead to positive outcomes. To the most part the outcome variables are either performance and user reactions (Howard & Rose, 2019). For example, in the seminal Goodhue and Thompson's (1995) on TTF, the authors found a positive relationship between utilisation and individual performance. Howard & Rose (2019) evaluated the effect of utilisation on user reactions which included perceived ease of use and relative advantage. In the case of smartwatch and given that our main focus is on continuous smartwatch use, performance is not deemed an appropriate outcome variable to measure as continuous use is also impacted by nonutilitarian reasons. Accordingly, we believe that user satisfaction as a more appropriate outcome variable to predict. As such, our third hypothesis is as follow:

H3 *Utilisation positively influences user Satisfaction with the smartwatch.*

Consistent with the above argument, we also attend to the recent research that suggests that people might adopt smartwatch not to use them to complete their tasks but to simply wear them as a fashion statement (see Iftikhar et al., 2020; Kim & Park, 2019; Nieroda et al., 2018). While such reasons might not lead to utilisation; it seems probable that if a smartwatch fits the adopter's identity, it will lead to a satisfaction. Accordingly, we conceptualise and specify a new fit construct, technology-identity-fit, to gauge the degree of alignment between the smartwatches hedonic fashion related features and the personality and identity of the beholder. Goodhue and Thompson's (1995) TTF model is expanded to incorporate this construct. Accordingly, our fourth hypothesis posits:
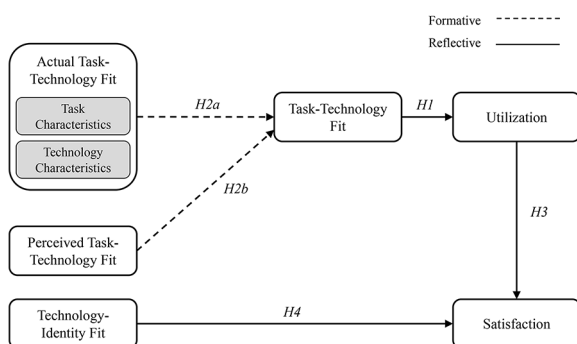

Fig. 1 Theoretical Model of Task-Technology-Identity-Fit

H4 *Technology Identity Fit, positively influences user Satisfaction with the smartwatch.*

The subsequent sections explain the methodology adopted to validate the above hypotheses and their strength of the overall theoretical model.

4 Research Methodology

This study is based on the well-established theory of TTF and aims to extend the concept of technology fit as a factor influencing outcomes emerging from user-technology interaction such as utilization and satisfaction. Therefore, the proposed model attempts to investigate, with a positivist stance, the role of fit as an antecedent to causal relationships with usability and satisfaction. Accordingly, the hypotheses are derived to test the theorised extensions rather than to explore phenomena that could lead to proposing new theory. The deductive nature of this study calls for a confirmatory method (Siponen & Klaavuniemi, 2020; Venkatesh et al., 2013) and therefore a systematic research methodology that acts as a blueprint for the research process deems most appropriate over other research methods (Chen & Hirschheim, 2004; Pinsonneault & Kraemer, 1993)). Such a method was developed and utilised during this research, as illustrated in Fig. 2.

4.1 Instrument Development

Online questionnaires in English and Arabic were used as the primary instruments to collect data from smartwatch users in Qatar. In order to operationalise the task and technology characteristics, our first attempt was to find an already used measure in the literature. We found only one paper that has such operationalisation (see Hsiao 2017). However, the author's operationalisation was limited to communication and information tasks. To ensure that we cover as much of the tasks and technology characteristics possible, we adopted the categories of smartwatch described in Visuri et al., (2017). Consequently, we reviewed the features available on smartwatch websites such as Apple's and Samsung's and identified all the relevant task characteristics and the corresponding tasks. Towards the end of this exercise, we were able to identify 17 technology characteristics and 17 corresponding user tasks organised under (1) Health and Activity Tracking, (2) Time, (3) Messaging, (4) Entertainment, (5) Phone Companion, (6) Customisation, and (7) Utility. The items are listed in the appendix. On the other hand, the operationalisation of Utilisation and TTF constructs followed those employed in Howard & Rose (2019) study. Pertaining to the TIF construct, we were inspired by the work of existing operationalisations (see Bölen 2020; Choi & Kim, 2016; Dehghani & Kim, 2019; Hsiao & Chen, 2018; Iftikhar et al., 2020; Jung et al., 2016; Nieroda et al., 2018) and developed a novel TIF measure. Finally, the satisfaction construct was operationalised in line with validated measures of satisfaction as found in the IS relevant literature (e.g. see Au et al., 2008; Bhattacherjee, 2001; McKinney et al., 2002).

The original language in which the questionnaire was developed is English. Thereafter, several rounds of translation into Arabic were done to target Arabic speaking participants too. In each translation round, parts of the
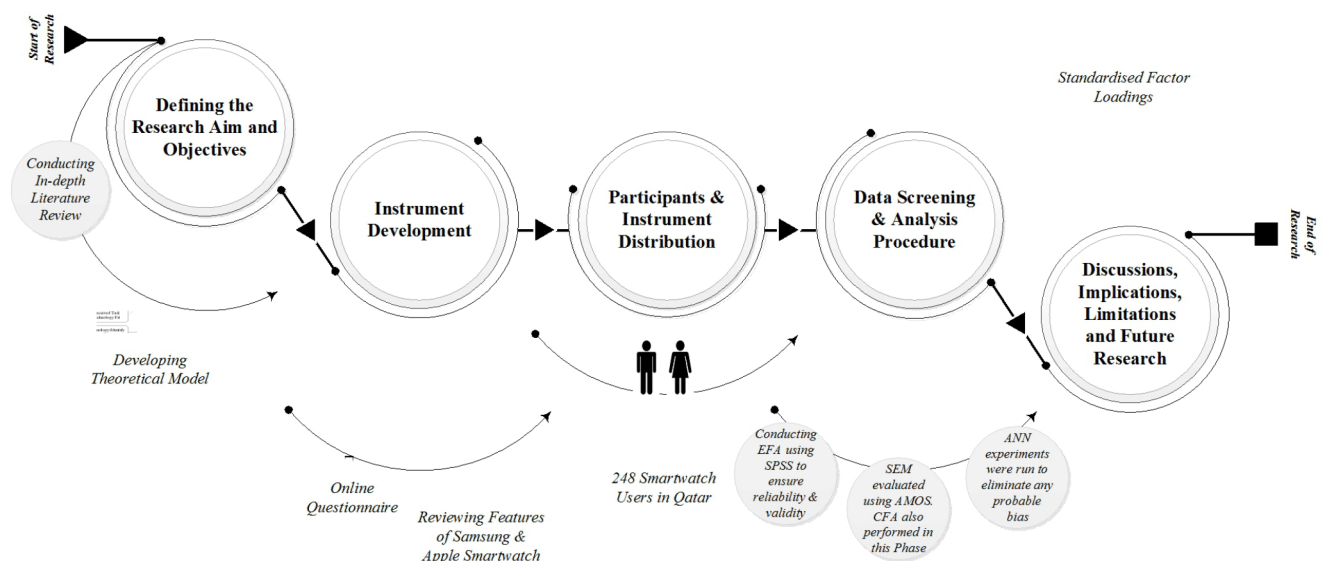

Fig. 2 Overall Research Methodology

questionnaire were translated by the authors into Arabic then translated back to English by an independent research assistant. Translation was adjusted as needed before starting another round. At the end, the whole questionnaire went under a full two-way translation process to ensure consistency between both languages and that questions are understood homogenously.

The questionnaire had two sections: demographic data and measurement items. Demographic data included respondents' gender, age group, occupation, nationality, cultural background, and the brand of smartwatch they own. The measurement items section incorporated questions on user satisfaction, utilisation, technology-identity-fit, and perceived task-technology-fit. Those constructs were measured by 5, 7, 6 and 4 items on a 5-point Likert scale, respectively. This section also had items that measure actual TTF that captured responders' frequency of performing tasks (e.g. reading emails) [Never…Always] and on responders' evaluation of their smartwatch features [Not Capable…Capable with too many features]. Each had 18 questions which were classified under seven categories. Table 1 lists and describes these task/feature categories.

Based on the designed instrument, task-technology-fit construct is assessed by two sub-constructs. The first sub-construct is respondents' self-reported perceived fit and the second is the actual fit. On the other hand, actual TTF for a given task is a compounded measurement calculated by multiplying the frequency of doing that task by the device's ability and features to perform that task. Therefore, each task question in the task characteristics subsection corresponded to a feature question in the technology characteristics subsection. Related questions were ordered in the same sequence in both subsections. Thereafter, for each task/ feature category, the average value of the corresponding multiplied items (from task characteristics and technology characteristics) is found to represent the actual TTF for that category. This is done according to the following formula where is the number of items in :

Therefore, actual task-technology-fit has seven calculated indicators.

The total number of questions was 58 (in addition to 7 questions for demographics data). The items of the administered questionnaire are provided in the appendix.

4.2 Participants and Instrument Distribution

Smartwatch adopters in Qatar were our target population. Therefore, smartwatch users were approached and invited to fill the questionnaire that was made available in Arabic and English. Snowballing was also used so participants could invite other potential participants such as friends and relatives who are also smartwatch users. Two trap questions

Table 1 Task Categories and Related Smartwatch Features

Task/Feature Category	Features Description (ability to)
Health	Measure vital signs and track physical activity.
Time	Tell time and alarms.
Communication/Smartphone Companion	Manage phone calls, notifications, emails and messages; integrate with social media.
Productivity	Manage contacts, task lists, and calendar.
Entertainment	Play music and games.
Utility	Display maps and navigation tools.
Customisation	Install additional apps and hardware customisation.

were also randomly added to the surveys to flag random responses. About 300 responses were collected, of which 248 were retained for analysis. Participants were given a brief introduction to the aims of the research so they knew why and how their input would be used. Particular attention was taken to keep this introduction neutral to avoid any bias that could lead to common method bias. The questionnaires clearly highlighted that participation was optional with the possibility to withdraw at any time and that no questions were mandatory.

4.3 Data Screening and Analysis Procedure

All responses having more than 20% of missing values or patterns of excessive repeated answers were discarded. Responses having wrong answers to the trap questions were also discarded. Missing values in the remaining dataset (0.5% of total answers) were imputed using mean values from other responses. After this screening process, 248 usable responses were retained for analysis. It is worth noting that the length of the questionnaire may have contributed to respondents abandoning filling the survey or randomly answering and therefore several responses had to be discarded.

Since new items were developed for this research, exploratory factor analysis (EFA) was conducted using SPSS to ensure the reliability and validity of the new scales and their fit with the other items in the survey. Subsequently, a Structural Equation Model (SEM) that reflects the theoretical model and the proposed hypotheses was evaluated using AMOS. Confirmatory factor analysis (CFA) was also performed during this phase. Lastly, multiple rounds of artificial neural network (ANN) experiments were run to eliminate any probable bias due to randomness used by ANN to optimise neurons' weights.

While SEM results can provide evidence for confirming/ negating proposed hypotheses based on the linear relationship between predicting and latent variables, ANN is not restricted to this linearity (Chong, 2013). The reason for

employing a two stage SEM and ANN approach in this study is threefold. Firstly, ANN can complement the output of the SEM analysis by examining the proposed hypotheses as non-linear relationships among the decision constructs (Yadav et al., 2016). Secondly, ANN can provide a ranked order of the relative influence of input factors on determining satisfaction with smartwatches (Liébana-Cabanillas et al., 2017). This is done by feeding the ANN with the significant factors identified in the SEM results and observing the normalised importance these factors have to predict satisfaction. Factors with prediction weights of 50% and above are considered strong predictors. Thirdly, the ability of ANN to perform non-parametric classification analysis on ordinal as well as nominal data can offer insights to understanding whether certain input features extracted from the predictive constructs can determine satisfaction or the choice of smartwatch, which is a nominal variable.

In order to achieve the ANN analysis, feed-forward with backpropagation multilayer perceptron (MLP) networks were used. This type of ANN is considered suitable for research in business and to predict dependent variables from identified independent variables (Chong, 2013; Priyadarshinee et al., 2017; Sharma et al., 2019).

5 Results

The process of data analysis yielded different types of results. The following subsections present those results in the same sequence of the analysis process phases.

5.1 Descriptive Statistics

Of the 296 collected responses, 248 were considered for analysis after screening out the invalid responses. Details on respondents' demographics are in Table 2 below.

5.2 Exploratory Factor Analysis and Scale Validation

Exploratory factor analysis was implemented using principal component analysis with Varimax rotation and Kaiser normalisation configurations. All items having factor loadings below 0.6 or with cross-loadings into more than one factor were discarded. Therefore, six items in total were removed from the analysis while each construct was still measured with three or more items. Four items were removed from the "Utilisation" construct, one from the "Perceived TTF" and one from the calculated "Actual TTF" (actual health_TTF). Table 3 shows the results of this analysis step. The Kaiser-Meyer-Olkin measure of sampling adequacy for the retained items was 0.89 and the Bartlett test of sphericity is significant at p-value < 0.01 indicating that the data is suitable

Table 2 Demographic Characteristics

Demographic Characteristics		
Gender	Females	59%
	Males	41%
Age Ranges	18-20	30%
	20-29	63%
	Over 30	7%
Occupation	Students	91%
	Professionals	9%
Nationality	Qatari	78%
	Arabs (non-Qatari)	15%
	Asians	4%
	Westerners	3%
Smartwatch Type	Apple	83%
	Others	17%

for EFA. Accordingly, five factors were distinguished, each corresponding to a construct in the theoretical model. The accumulative variance explained was 70.7%.

Discriminant and convergent validity tests as well as reliability analysis were done for the five constructs. The results of these are presented in Table 4. The average variance extracted (AVE) for all factors were above 0.5 and the square root of each AVE was higher than the correlation with other factors. Furthermore, the AVE of each factor was

Table 3 EFA Factor Loadings

Item	Component				
	1	*2*	*3*	*4*	*5*
Sat1	0.797				
Sat2	0.785				
Sat3	0.788				
Sat4	0.847				
Sat5	0.803				
Util2		0.821			
Util3		0.600			
Util5		0.656			
TIF1			0.735		
TIF2			0.831		
TIF3			0.663		
TIF4			0.825		
TIF5			0.632		
TIF6			0.600		
Perceived_TTF1				0.784	
Perceived_TTF2				0.822	
Perceived_TTF3				0.717	
Actual_TTF1 (Messaging)					0.887
Actual_TTF2 (Phone Companion)					0.873
Actual_TTF3 (Entertainment)					0.814
Actual_TTF4 (Utility)					0.787
Actual_TTF5 (Customization)					0.760
Actual_TTF6 (Time)					0.674

Table 4 Results of Reliability and Validity Tests

Correlations					AVE	CR
	Satis-faction	Util-isation	Per-	TIF		
Satis-faction						
Util-isation						
Per-						
TIF	0.586	0.208	0.338	0.447 0.715	0.511	0.343 0.873 0.860

*. below 0.7

higher than the maximum-shared variance (MSV). Therefore, the extracted factors fulfilled the discriminant and convergent validity requirements. In terms of scale reliability, Cronbach's Alpha values for each extracted factor were calculated and they were all above 0.7, except for utilisation that scored 0.65 that is still within the acceptable range (Taber, 2018). The factors' composite reliabilities (CR) were above 0.6 confirming the internal consistency of scale items Finally, Herman's common factor analysis was run to test the common method bias in the data. When forcing all items to load on one factor, using PCA and no rotation, the model explains only 36.9% of total variance, which is comfortably below 50%.

5.3 Measurement Model

The five constructs with twenty-three items were fed into AMOS for confirmatory factor analysis. A second-order construct, TTF, formed by perceived_TTF and actual_TTF was created to match the theoretical model. The model identification rule stating that each factor should have a minimum of two indicators in the standard CFA model (Kline, 2011) was satisfied. No items were found to covary with other constructs than its respective one. Additionally, it was not necessary to remove any items in order to improve the model fit. The ratios of chi-square to degrees of freedom (CFMIN/DF), GFI, NFI, CFI, RMSEA, RMR and SRMR were 1.301, 0.88, 0.9, 0.974, 0.042, 0.416, and 0.08, respectively. These figures indicate satisfactory model fit.

5.4 Structural Model

The structure model included the direct effects of independent constructs on the dependent ones: utilisation and satisfaction. The total variance explained by the model for utilisation and satisfaction was 0.47 and 0.62, respectively. Table 5 below summarises the standardised regression weights observed between constructs. All regression weights were significant at p-value < 0.01, thus hypotheses can be evaluated against the regression weights at a 99% confidence level.

From the path analysis results, all hypotheses are confirmed at the stated level of statistical significance. Figure 3 shows the theoretical model with the standardised factor loadings of the direct effects. It also displays R^2 values for both utilisation and satisfaction constructs.

While EFA clearly distinguished between Perceived_TTF and Actual_TTF as being two separate constructs, CFA confirmed they are part of TTF in spite of the higher effect of Perceived_TTF. To further test hypothesis H2, the structural model was altered by omitting the Actual_TTF construct and therefore leaving TTF to be expressed only through Perceived_TTF. While the overall goodness of fit of the resulting model was satisfactory, this led to a significant drop in the total explained variance of utilisation, from 0.47 to 0.29. Furthermore, the standardised regression weight between TTF and utilisation dropped from 0.682 to 0.54.

5.5 Classification with ANN

Two types of analysis were conducted using multilayer perceptron neural networks. The first was to confirm the

Table 5 Standardised Regression Weights between Constructs

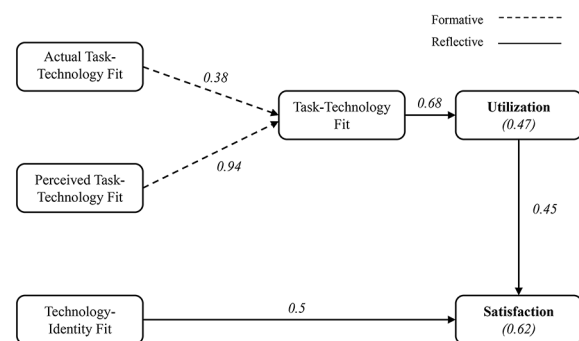| Hypothesis	Path	Standardised Regression Weight	P-value	Status
H1	TTF -> Utilisation	0.683	>0.01	Accepted
H2a	Actual_TTF -> TTF	0.382	>0.01	Accepted
H2b	Perceived_TTF -> TTF	0.937	>0.01	Accepted
H3	Utilisation -> Satisfaction	0.450	>0.01	Accepted
H4	TIF -> Satisfaction	0.500	>0.01	Accepted

Fig. 3 Standardised Factor Loadings

findings from the SEM analysis in terms of evaluating the proposed model where linear and non-linear relationships between predictive constructs and the latent construct are examined. The second analysis was to eventually predict the type of smartwatch (Apple Watch vs. Other), which is a categorical variable, from the constructs of the proposed theoretical model. For both types of analysis, the dataset was split into 70% and 30% for training and testing, respectively.

5.5.1 Predicting Satisfaction

Since the SEM analysis confirmed that all constructs in the theoretical model are statistically significant, four observed constructs (Actual_TTF, Perceived_TFF, Utilisation and TIF) were used as predictive indicators for the latent variable Satisfaction. The ANN had four neurons in the input layer, a neuron per predictive constructs, one neuron in the output layer corresponding to the latent construct, satisfaction, and a single hidden layer.

Table 6 below shows a summary of the results obtained from running ten iterations of the specified network. The accuracy of the ANN results was evaluated using the root-mean-square-error (RMSE), which is defined as the average difference between predicted values and the actual values of the latent construct. All RMSE values during training and testing the ANN were relatively small and acceptable under 0.5 thus indicating a relatively good fit of the prediction model. Sensitivity analysis was also done to rank the relative importance of the predictive factors.

In all iterations, TIF proved to be the dominating factor in terms of prediction power. Perceived_TTF and Utilisation shared the second and third rank with a relative prediction importance above 50%. Actual_TTF was not a strong predictor where its relative importance never crossed the limit of 50%. These results correspond to the findings of the SEM analysis.

5.5.2 Predicting Smartwatch Type

Using the five main factors from the theoretical model as predictors, ANN experiments were run as an attempt to predict the choice of smartwatch users make. Given that the majority of respondents were Apple Watch users, the problem at hand was to properly classify the smartwatch type into two classes labeled "Apple Watch" and "Other" using Actual TTF, Perceived TTF, TIF, Utilisation and Satisfaction as input. Therefore, the ANN used had five input neurons, one hidden layer and two output neurons, one per smartwatch category. Ten iterations of ANN were run. Classification accuracy ranged between 85% and 100% for correctly predicting "Apple Watch" observations; however, prediction accuracy for "Other" did not exceed 25%. This might be attributed to the limited number of observations to conduct classification with ANN and to the disproportion in the number of observations between both classes.

Moreover, sensitivity analysis was performed for each iteration to rank the effect of each input factor in predicting the smartwatch type. In the majority of the rounds (8 out of 10), actual TTF was the strongest predictor followed by perceived TTF. Satisfaction and TIF shared the third rank, while utilisation was not a strong classification predictor.

6 Discussion

The main premise of this research is that users' satisfaction with the devices they wear can be better understood if we evaluate how this technology fits with their utilitarian and identity needs. Accordingly, we adapted the well established TTF theory of Goodhue & Thompson (1995) and expanded their notion of fit to include a new construct –TIF – that gauges the degree of fit between the technology and user identity. To this end, our study provided support of the

Table 6 Results ANN Analysis to Predict Satisfaction

RMSE			Ranking of Factor Importance			
Iteration	*Training*	*Testing*	*#1*	*#2*	*#3*	*#4*
Iteration-1	0.271	0.230	TIF	Util	P_TTF	A_TTF*
Iteration-2	0.239	0.217	TIF	Util	P_TTF	A_TTF*
Iteration-3	0.239	0.343	TIF	P_TTF	Util	A_TTF*
Iteration-4	0.221	0.403	TIF	P_TTF	Util	A_TTF*
Iteration-5	0.275	0.161	TIF	P_TTF	Util	A_TTF*
Iteration-6	0.225	0.204	TIF	P_TTF	Util	A_TTF*
Iteration-7	0.256	0.258	TIF	P_TTF	Util	A_TTF*
Iteration-8	0.262	0.327	TIF	P_TTF	Util	A_TTF*
Iteration-9	0.266	0.272	TIF	P_TTF	Util	A_TTF*
Iteration-10	0.269	0.145	TIF	P_TTF	Util	A_TTF*
Average	*0.252*	*0.256*	*TIF*	*P_TTF*	*Util*	*A_TTF**
S.D.	*0.019*	*0.078*				

Util: Utilisation, P_TTF: Perceived TTF, A_TTF: Actual TTF. *. Relative importance < 0.5

significance of the TIF construct, both statistically and in terms of effect size, in explaining satisfaction. In fact, coefficients of determination (R^2) demonstrated by the model show good predictive power. 62% of variance in satisfaction could be captured by the task-technology-fit and technology-identity-fit constructs. Interestingly, both fit constructs proved to have quasi-equal effects on satisfaction. This denotes the importance of the non-utilitarian features of smartwatches which is consistent with existing research on smartwatches (see Bölen 2020; Choi & Kim, 2016; Dehghani & Kim, 2019; Hsiao & Chen, 2018; Iftikhar et al., 2020; Jung et al., 2016; Nieroda et al., 2018).

Evidently, the impact of the non-utilitarian features of wearable devices have been previously incorporated into theoretical models such as TAM (see Bölen, 2020) and UTAUT2 (see Dehghani et al., 2018) to help explain outcome variables like satisfaction or continuous intention to use, respectively. Still, when comparing the path coefficients between nonutilitarian technology characteristics and outcome variables like satisfaction (in Bölen, 2020) or continuous intention to use (Dehghani et al., 2018), it is evident that our technology-identity-fit construct can better explain satisfaction. Those results are consistents with the premises of Goodhue & Thompson (1995), Cane & McCarthy (2009) and Dishaw & Strong (1998) on the predominance of fit models in predicting positive outcomes such as user reactions, performance, and satisfaction. Today's wearable technologies that tightly interact with consumers must possess the ability to fit in with the wearer's style and personality to achieve satisfaction. Indeed, the availability of smartwatches in different colors and the ability to personalise them with accessories, such as straps, play a considerable role to make the look and feel of the device aligned with the wearer's preferences.

Albeit task-technology-fit was deemed as a suitable theory to guide our investigation, the way the TTF construct has been used in the literature receives considerable criticism in the IS literature. Indeed, a more recent article by Howard & Rose (2019) describes the flaws in the existing conceptualization and operationalization of TTF. One main criticism stems from the difficulty in matching all characteristics of the technology with the tasks conducted by the users which results in the inability of the construct to capture the entire scope of TTF. Given that the technology at hand – smartwatch – is a versatile technology, it is packed with a large variety of features that may be underutilised by the majority of users. Furthermore, users with certain profiles and purposes tend to use different functionalities from those used by other users. Therefore, a clear line should be drawn to distinguish the use of a feature in a versatile technology or the whole tool itself. This is notably pertinent to assessing users' opinions on their technology gadgets. The

confusion resulting from mixing between evaluating a given feature, or set of features, and the tool itself may also lead to inaccurate, and even invalid, insights. This phenomenon was noticed during this research on two occasions; when measuring utilisation and when forming the TTF construct from actual and perceived TTF. First, utilisation construct suffered from good internal consistency (0.65 for Cronbach's Alpha indicator) albeit its items were borrowed from existing and well-established questionnaires (see Howard & Rose 2019). This might be attributed to respondents' answers to the questions measuring utilisation. While some answers might have been for the features the respondent regularly uses, other answers might have referred to the whole tool (i.e. smartwatch). Second, the perceived TTF had a much larger effect than the actual TTF when it comes to form the TTF construct. Those results are consistent with what Howard & Rose (2019) found when comparing the relevance of perceived and actual task-technology constructs in the IS literature. In the context of smartwatches, this can be explained by the tendency of users to report fit based on their own experience with the features they regularly use whereas actual fit targets all feature categories of a typical smartwatch. Therefore, overestimating fit. Nevertheless, actual TTF is still a significant indicator of the overall TTF construct, even if the results showed that it has a relatively weak size effect.

In order to address this issue; i.e., the inability to capture the full scope of TTF when matching tasks to the features of the technology, we followed Howard & Rose (2019) suggestion pertaining to the use of the overarching perceived TTF construct. However, to ensure that users do not conflate their perception of fit of the technology with the tasks they perform with other nonutilitarian features, we opted to specify TTF as comprised of both perceived and actual fit. Accordingly, the EFA we performed clearly distinguished between Perceived_TTF and Actual_TTF as being two separate constructs, CFA confirmed they are part of TTF in spite of the higher effect of Perceived_TTF. To further test hypothesis H2, the structural model was altered by omitting the Actual_TTF construct and therefore leaving TTF to be expressed only through Perceived_TTF. While the overall goodness of fit of the resulting model was satisfactory, this led to a significant drop in the total explained variance of utilisation, from 0.47 to 0.29. Furthermore, the standardised regression weight between TTF and utilisation dropped from 0.682 to 0.54. Our results show that the perceived TTF has a much larger effect than the actual TTF when it comes to form the TTF construct. Those results are consistent with what Howard & Rose (2019) found when comparing the relevance of perceived and actual task-technology constructs in the IS literature. In the context of smartwatches, this can be explained by the tendency of users to report fit based on

their own experience with the features they regularly use whereas actual fit targets all feature categories of a typical smartwatch. Therefore, overestimating fit. Nevertheless, actual TTF is still a significant indicator of the overall TTF construct, even if the results showed that it has a relatively weak size effect. As such, the obtained results supported hypothesis H2 stating the significance effect of actual TTF as a dimension of TTF when it comes to explain utilisation. This comes in line with Howard & Rose (2019) recommendations of TTF evaluation.

Pertaining to the multi-method approach taken in this research, our results were consistent for both SEM and ANN. Indeed, both methods complemented each other to explain the underlying effects of technology fit on satisfaction. While SEM results suggested that effect of TIF on satisfaction may be slightly higher than the effects of utilisation solely, ANN concluded the clear dominance of fit with identity to predict satisfaction. ANN also positioned perceived fit with tasks in second position to predict users' satisfaction. This also comes in line with the SEM results where TTF, which affects utilisation, was better predicted by perceived TTF compared to the actual fit. Actual TTF did not demonstrate significant effect on satisfaction though. Conversely to the case of examining satisfaction, actual TTF proved to be the strongest predictor when it comes to the choice of smartwatch. This can be explained by the necessity of compatibility of the smartwatch with the user's smartphone to be useful. While most smartwatches (e.g. Apple Watch and Samsung smartwatches) offer similar functionalities, they differ in terms of compatibility with smartphones of the respective brands. This is further highlighted by the fact that smartwatches are considered secondary devices and have to be paired as companions to compatible smartphones. In fact, at the time of this writing, Apple Watch can only be normally paired to iPhone devices. Therefore, compatibility is crucial to harness the utilitarian functionalities of a smartwatch, especially those relevant to tasks related to the smartphone such as notifications, messaging and phone calling. In other words, regardless of the personalisation capabilities of a smartwatch, its aesthetic look, and match with a user identity, utility plays the biggest role in the choice of a smartwatch.

Interestingly, while the first part of the ANN analysis validated the findings from the SEM analysis and stressed the marginal effect of actual TTF on satisfaction, the second part attributed a considerable importance to that construct. This may explain the chronological importance of each aspect of TTF, actual and perceived. In fact, satisfaction and perception may only be expressed after adopting and using an artefact, whereas the choice of that artefact comes before use. This is notably true if the alternative options have similar functionalities but differ in non-utilitarian features. For instance, both Apple Watch and Samsung Galaxy Watch expose very similar sets of features; however, an Android smartphone owner would rationally not choose to adopt an Apple Watch, even if esthetically it may look appealing for that individual. This is simply because many of the Apple Watch utility functionalities will be unusable due to incompatibility with the smartphone. Such a decision need not to be perceived after use, but to actually fit the features of the smartwatch with the tasks the user wants to do with the device. Such a judgment can be done prior adoption, hence the importance of the actual TTF in the smartwatch choice.

7 Implications and Limitations

7.1 Theoretical Implications

Wearables like smartwatches, smart glasses, and smart fabrics embody personality-related features that distinguish them from other technologies. The sociomaterial entanglement of people with wearables necessitates a better understanding of how they fit in our lives; not only in terms of their utility but also style. Such wearables impose new assumptions on technology adoption and widen the research boundaries to encompass fashionology. Hence, theoretical models to investigate the adoption and continuous use of such technologies must include novel factors related to adopters' styles and the technology's fashion trends. Our theoretical model clearly explains that people can be satisfied by their smartwatch; either because the technology fits the tasks they do, because it fits with their identity, or both. When the technology fits their tasks, they end up using it rendering them satisfied. When the technology fits with their identity, they can be satified as well even if they don't necessarily use it.

Notwithstanding, the value that acceptance theories such as UTAUT and TAM and fit theories such as TTF afford, we reckon that our proposed theoretical fit model that account for contemporary realities as the primary implications from a theoretical perspective. Specifically, the theoretical model we propose not only guages the degree of fit between the task and technology but also between technology and identify and can better explain the type of smartwatches adopters choose. Our prrposed model was inspired by research conducted by Wu & Chen (2017), Choi & Kim (2016), Hsiao & Chen (2018), Dehghani et al., (2018), and Iftikhar et al., (2020) who accentuated the role of the technology's nonutilitarian features as well as the adopter's identity as important predictors of techology choices.

Reconceptualising the fit between the tasks users perform with the smartwatch features included not only self-reported percieved fit but also actual fit. This constitutes another

contribution to IS theory. Accordingly, our research answers calls in the literature to evaluate task-technology fit holistically by incorporating actual and percieved fit, which is considered a better predictor of utilisation (Howard & Rose, 2019).

7.2 Methodological Implications

This paper also presents several contributions to the methodology employed when it comes to study satisfaction from a fit point of view. *Firstly*, a new instrument was developed and validated to assess satisfaction with TTF and TIF predictors. The instrument included the necessary items to assess TTF as a compounded construct formed by both perceived TTF and calculated actual TTF. It is described, tested and validated how measuring Actual TTF was done. A similar approach can be reproduced in other studies targeting TTF of other versatile technologies. *Secondly*, while this paper used a traditional approach of factor analysis to validate the model, where EFA was used to validate the instrument and CFA to test the model fit and hypotheses, ANN was applied as a second layer of analysis to confirm the factor analysis results. This allowed to capture not only linear relationships between constructs but also non-linearity. *Finally*, ANN was also used to predict a categorical variable, the smartwatch type, from the theoretical model constructs. To the best of authors' knowledge, this study is the first to have applied such a hybrid SEM-ANN methodology to assess satisfaction with smartwatch use and to predict smartwatch type as a classification problem addressed by ANN.

7.3 Practical Implications

The insights offered in this research provide several values and hints to smartwatch vendors and other emerging players in the smartwatch industry. In fact, the ability to personalise smartwatches with accessories enables access to important new entrants in the smartwatch industry such as accessory vendors, marketers and distributers. Emphasizing customization and personalization of smartwatches to fit with users' identity plays a significant role on improving satisfaction, and consequently, sustaining customer loyalty. This is particularly crucial to vendors in today's competitive technology market. Besides, the importance of technology-identity fit, as proven in this study, may pave the way to new marketing strategies leading to new sale leads. This lead to conclude that conceiving new ways to further personalise smartwatches will clearly overcome utilitarian features. This is particularly a valid assumption since all modern smartwatches offer similar mature and taken-for-granted functionalities, reducing the utilitarian differences between smartwatch brands and models. On the other hand, it would

give opportunities to fashion in overtaking the drive of the smartwatch market by making the choice of smartwatch greatly based on the brand and the degree of customisation and personalization, which are two concepts closely related to user identity.

Another contribution relates to the key factors that influence users' choice of smartwatches. The compatibility constraints imposed by Apple on its current watches so that they can only be paired with iPhone devices may hinder potential adopters who are using Android smartphones. Relaxing such a restriction by Apple may give even more importance to the fashion aspect of smartwatches in the purchase decision as such a decision will not be affected by functional or technical constraints. Therefore, luxury brands might have an important role in that shift that is still highly technological. Decoupling smartwatches from smartphones, or their operating systems, and granting them the status of autonomous connected smart devices might be expected just as it has been previously the case for smartphones with computers. Such a change would transform the whole perception of smartwatches and further increase their proliferation.

7.4 Limitations and Future Work

From a theoretical viewpoint, the technology-identity fit construct relied solely on subjects' perception and did not have an actual fit dimension, unlike TTF. Such an addition to the model may better reflect the technology-identity fit construct, which in turn may have a different causal effect on satisfaction with smartwatch use. Another limitation can be attributed to the sample used to validate the model. Convenient sampling had to be employed where sample biases were observed such as in age groups and type of smartwatches. A more homogeneous sample may hold better insights concerning the other type of smartwatches, especially when it comes to neural network analysis. Lastly, the sample size is relatively small to conduct neural network analysis that would lead to more accurate outcomes. This is particularly pertinent to the classification process aiming to predict the type of smartwatch a user may choose. While the prediction accuracy for Apple watches was satisfactory, it was on the account of poorly predicting other smartwatches.

Avenues for future works include addressing the limitations of this study and to consider an international sample that is not specific to a particular context. Repeating this cross-sectional study with an enhanced model and a larger sample size may also be part of a larger longitudinal study examining the role of smartwatch utilitarian and non-utilitarian features and their fit with individuals use cases and identity on users' satisfaction.

8 Conclusions

Sensors are getting cheaper and tinier by the day and so are processors, storage devices and displays. As a result, many novel consumer products that were deemed infeasible to produce a few years back are now available in the market and are being adopted at fast rates. Wearables like smartwatches, smart glasses, or smart textiles belong to this category of technologies. Yet wearables possess an amplified trait of persona. People greatly identify themselves with what they wear. People are unlikely to carry a laptop or a smartphone around only to express their identity. If they carry a technology, they mean to use it. This is not necessarily the case of wearable technologies. Adopters wear them. Hence, it can indeed be for either reason or both. Out study explains how these technologies fit into the daily life of the current adopters; be it their identity or their routines. Moreover, the results expose the technology characteristics, both practical and non-utilitarian, that are deemed most important to satisfy adopters. Industry leaders such as Apple and Samsung can make use of our results and tailor their product features to be aligned with the consumer requirements, especially in terms of customisation and personalisation.

9 Appendix – Survey Items

Demographics:

1. Please specify your: country of residence.
2. Please specify your: gender.
3. Please specify your: nationality.
4. Please specify your: culture group.
5. Please specify your: profession.
6. Do you have a smartwatch?
7. If you have a smartwatch, what brand is it (e.g. Apple, Samsung, and Fitbit)?

Measurement Items:

1. **Questions related to tasks characteristics (5-point Likert scale: 1-never, 5-always).**

    a. Health and Activity Tracking Tasks.

      i. *Regardless of the tool I use, I check: My physical activity (e.g. steps I walked).*
      ii. *Regardless of the tool I use, I check: My health condition (e.g. heart rate).*

    b. Time Tasks.

      i. *Regardless of the tool I use, I check: The time.*
      ii. *Regardless of the technology I use, I: Use alarms.*
      iii. *Regardless of the tool I use, I check: Time in other time zones.*

    c. Messaging Tasks.

      i. *Regardless of the tool I use, I check: Social media notifications.*
      ii. *Regardless of the technology I use, I: Read my emails and the messages I receive.*
      iii. *Regardless of the technology I use, I: Compose/ reply to emails and send messages (e.g. SMS).*
      iv. *Regardless of the technology I use, I: Post on social media (e.g. Twitter, Facebook).*

    d. Entertainment Tasks.

      i. *Regardless of the technology I use, I: Entertainment (movie & music players).*

    e. Phone Companion Tasks.

      i. *Regardless of the technology I use, I: Receive and place phone calls.*
      ii. *Regardless of the technology I use, I: Manage my contacts (create, edit, search).*
      iii. *Regardless of the technology I use, I: Scheduling meetings & managing my calendar.*
      iv. *Regardless of the technology I use, I: Setting up reminders and task lists.*
      v. *Regardless of the technology I use, I: Virtual assistants (e.g. Siri, Alexa).*

    f. Customization Tasks.

      i. *In general: I customize my electronic devices (e.g. computer, smartphone).*
      ii. *Regardless of the technology I use, I: Install new applications on my smartphone and computer.*

    g. Utility Tasks.

      i. *Regardless of the technology I use, I: Maps tools (e.g. Google Maps).*

2. **Questions related to technology functional characteristics (5-point Likert scale: 1-Not capable, 5-Capable with too many features).**

a. Health and Activity Tracking Characteristics.

    i. *How capable is your smartwatch in: Checking physical activities (e.g. steps counter).*
    ii. *How capable is your smartwatch in: Checking health conditions (e.g. heart rate).*

b. Time Characteristics.

    i. *How capable is your smartwatch in: Telling the time.*
    ii. *How capable is your smartwatch in: Setting alarms.*
    iii. *How capable is your smartwatch in: Telling the time in other time zones.*

c. Messaging Characteristics.

    i. *How capable is your smartwatch in: Notifying you of emails.*
    ii. *How capable is your smartwatch in: Reading emails & messages and social media feeds.*
    iii. *How capable is your smartwatch in: Send emails or messages (e.g. SMS).*
    iv. *How capable is your smartwatch in: Post on social media (e.g. Twitter, Facebook).*

d. Entertainment Characteristics.

    i. *How capable is your smartwatch in: Entertaining you (e.g. playing videos, music, games))*

e. Phone Companion Characteristics.

    i. *How capable is your smartwatch in: Receiving and placing phone calls.*
    ii. *How capable is your smartwatch in: Managing your contacts (create, edit, search).*
    iii. *How capable is your smartwatch in: Scheduling meetings & showing your calendar.*
    iv. *How capable is your smartwatch in: Creating to do lists.*
    v. *How capable is your smartwatch in: Virtually assisting you (e.g. Siri, Alexa).*

f. Customization Characteristics.

    i. *How capable is your smartwatch in: Changing colors.*
    ii. *How capable is your smartwatch in: Installing new apps.*

g. Utility Characteristics.

    i. *How capable is your smartwatch in: Helping you navigate with maps (e.g. Google Maps).*

3. **Task Technology Fit (5-point Likert scale: 1-strongly disagree, 5-strongly agree).**

a. *My smartwatch: Matches the task(s) that I need to do.*
b. *My smartwatch: Is in synch with the task(s) that I need to do.*
c. *My smartwatch: Has the exact functions needed for the tasks that I need to do.*
d. *In general: The tasks I do match the features of my smartwatch.*

4. **Technology Identity Fit (5-point Likert scale: 1-strongly disagree, 5-strongly agree).**

a. *My Smartwatch: Matches my style.*
b. *My Smartwatch: Reflects my identity.*
c. *My Smartwatch: Makes me look good.*
d. *My Smartwatch: Reflects the kind of person that I am.*
e. *My Smartwatch: Is accessorizable (e.g. straps, skins, covers) to reflect my style.*
f. *My Smartwatch: Is customizable (e.g. faces, screens) to match with my style.*

5. **Utilisation (5-point Likert scale: 1-strongly disagree, 5-strongly agree).**

a. *Express your opinion on the following : I wear my smartwatch most of the time.*
b. *Express your opinion on the following : I wear my smartwatch only to do specific tasks.*
c. *Express your opinion on the following : I cannot imagine doing my task(s) without using my smartwatch.*
d. *Express your opinion on the following : I use my smartwatch to complete my task(s).*
e. *Express your opinion on the following : I rarely perform my task(s) without using my smartwatch.*
f. *Express your opinion on the following : I prefer using my smartphone or computer to perform my tasks.*
g. *Express your opinion on the following : I wear my smartwatch only because it looks good.*

6. **Satisfaction (5-point Likert scale: 1-strongly disagree, 5-strongly agree).**

a. *Express your opinion on the following : I am satisfied with my smartwatch.*

b. *Express your opinion on the following : I am pleased to use my smartwatch.*

c. *Express your opinion on the following : It is delightful to use my smartwatch.*

d. *Express your opinion on the following : I am satisfied with the use of my smartwatch.*

e. *Express your opinion on the following : I like my smartwatch.*

Declarations

Conflict of Interest The authors confirm that there is no conflict of interest.

References

Adapa, A., Nah, F., Hall, R., Siau, K., & Smith, S. (2018). Factors Influencing the Adoption of Smart Wearable Devices. *International Journal of Human - Computer Interaction*, 34(5), 399–409

Al-Emran, M. (2021). Evaluating the Use of Smartwatches for Learning Purposes through the Integration of the Technology Acceptance Model and Task-Technology Fit.International Journal of Human–Computer Interaction,1–9

Al-Maatouk, Q., Othman, M. S., Aldraiweesh, A., Alturki, U., Al-Rahmi, W. M., & Aljeraiwi, A. A. (2020). Task-technology fit and technology acceptance model application to structure and evaluate the adoption of social media in academia. *IEEE Access*, 8, 78427–78440

Au, N., Ngai, E. W., & Cheng, T. E. (2008). Extending the understanding of end user information systems satisfaction formation: An equitable needs fulfillment model approach.Mis Quarterly,43–66

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model.MIS Quarterly,351–370

Bölen, M. C. (2020). Exploring the determinants of users' continuance intention in smartwatches. *Technology in Society*, 60, 101209

Bravo, E., & Bayona, H. (2020). *Explaining multidimensional Facebook benefits: A task-technology fit approach.* Paper presented at the Proceedings of the 53rd Hawaii International Conference on System Sciences

Brodsky, A. (2021). Virtual surface acting in workplace interactions: Choosing the best technology to fit the task. *Journal of Applied Psychology*, 106(5), 714

Brown, D. (2020). *Apple dominates the smartwatch market as sales rise despite COVID-19 pandemic*. USA Today

Cane, S., & McCarthy, R. (2009). Analysing the factors that affect information systems use: a task-technology fit meta-analysis. *Journal of Computer Information Systems*, 50(1), 108–123

Chen, W., & Hirschheim, R. (2004). A paradigmatic and methodological examination of information systems research from 1991 to 2001. *Information systems journal*, 14(3), 197–235

Choi, J., & Kim, S. (2016). Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use smartwatches. *Computers in Human Behavior*, 63, 777–786

Chong, A. Y. L. (2013). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption. *Expert Systems with Applications*, 40(4), 1240–1247

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of

usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, 65, 276–284

Clermont, C. A., Duffett-Leger, L., Hettinga, B. A., & Ferber, R. (2020). Runners' Perspectives on 'Smart' Wearable Technology and Its Use for Preventing Injury. *International Journal of Human - Computer Interaction*, 36(1), 31–40

Curry, D. (2015). Apple watch hits 10,000 apps: How do android wear, pebble, and Samsung compare? *Digital Trends.*

Dang, Y. M., Zhang, Y. G., Brown, S. A., & Chen, H. (2020). Examining the impacts of mental workload and task-technology fit on user acceptance of the social media search system. *Information Systems Frontiers*, 22(3), 697–718

Dehghani, M. (2016). *An assessment towards adoption and diffusion of Smart Wearable technologies by consumers: The cases of smart watch and fitness wristband products.* Paper presented at the CEUR Workshop Proceedings

Dehghani, M. (2018). Exploring the motivational factors on continuous usage intention of smartwatches among actual users. *Behaviour & Information Technology*, 37(2), 145–158

Dehghani, M., Kim, K. H., & Dangelico, R. (2018). Will smartwatches last? Factors contributing to intention to keep using smart wearable technology. *Telematics and Informatics*, 35(2), 480–490

Dehghani, M., & Kim, K. J. (2019). The effects of design, size, and uniqueness of smartwatches: perspectives from current versus potential users. *Behaviour & Information Technology*, 38(11), 1143–1153

Dishaw, M. T., & Strong, D. M. (1998). Assessing software maintenance tool utilization using task–technology fit and fitness-for-use models. *Journal of Software Maintenance: Research and Practice*, 10(3), 151–179

Dutot, V., Bhatiasevi, V., & Bellallahom, N. (2019). Applying the technology acceptance model in a three-countries study of smartwatch adoption. *The Journal of High Technology Management Research*, 30(1), 1–14

Ernst, A. W., & Ernst, C. P. H. (2016). Success comes to those who are successful: the influence of past product expectation confirmation on smartwatch usage. *In The Drivers of Wearable Device Usage* (pp. 49–58). Springer, Cham.

Erskine, M. A., Khojah, M., & McDaniel, A. E. (2019). Location selection using heat maps: Relative advantage, task-technology fit, and decision-making performance. *Computers in Human Behavior*, 101, 151–162

Fillieri, R., Chen, W., & Dey, B. L. (2017). The importance of enhancing, maintaining and saving face in smartphone repurchase intentions of Chinese early adopters: an exploratory study. *Information Technology and People*, 30(3), 629–652

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Reading, MA: Addison-Wesley.

Gao, Y., He, L., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, 115(9), 1704–1723

Ghahramani, F., & Wang, J. (2019). Impact of Smartphones on Quality of Life: A Health Information Behavior Perspective. *Information Systems Frontiers*, 22, 1275–1290

Goodhue, D. L. (1998). Development and measurement validity of a task-technology fit instrument for user evaluations of information system. *Decision sciences*, 29(1), 105–138

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance.Mis Quarterly,213–236

Gu, Z., Wei, J., & Xu, F. (2016). An empirical study on factors influencing consumers' initial trust in wearable commerce. *Journal of Computer Information Systems*, 56(1), 79–85

Heine, M. L., Grover, V., & Malhotra, M. K. (2003). The relationship between technology and performance: a meta-analysis of technology models. *Omega*, 31(3), 189–204

Hong, J. C., Lin, P. H., & Hsieh, P. C. (2017). The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch. *Computers in Human Behavior*, 67, 264–272

Howard, M. C., & Rose, J. C. (2019). Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. *Information & Management*, 56(6), 103134

Hsiao, K. L. (2017). What drives smartwatch adoption intention? Comparing Apple and non-Apple watches. *Library Hi Tech*, 35(1), 186–206

Hsiao, K. L., & Chen, C. C. (2018). What drives smartwatch purchase intention? Perspectives from hardware, software, design, and value. *Telematics and Informatics*, 35(1), 103–113

Iftikhar, H., Shah, P., & Luximon, Y. (2020). Exploring the balance between utilitarian and hedonic values of wearable products. In: *Vol. 967. Advances in Intelligent Systems and Computing* (pp. 407-416)

Jeong, H., Kim, H., Kim, R., Lee, U., & Jeong, Y. (2017). Smartwatch wearing behavior analysis: a longitudinal study. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1*(3), 1-31

Joo, J., & Sang, Y. (2013). Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory. *Computers in Human Behavior*, 29(6), 2512–2518

Jung, Y., Kim, S., & Choi, B. (2016). Consumer valuation of the wearables: The case of smartwatches. *Computers in Human Behavior*, 63, 899–905

Kim, & Park, E. (2019). Beyond coolness: Predicting the technology adoption of interactive wearable devices. *Journal of Retailing and Consumer Services*, 49, 114–119

Kim, & Shin, D. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research*, 25(4), 527–541

Klinker, K., Berkemeier, L., Zobel, B., Wüller, H., Huck-Fries, V., Wiesche, M., & Krcmar, H. (2018). Structure for innovations: A use case taxonomy for smart glasses in service processes. *Multikonferenz Wirtschaftsinformatik Lüneburg, Deutschland*

Krey, N., Hui-Wen, S., Ramayah, C., T., & Rauschnabel, P. A. (2019). How functional and emotional ads drive smartwatch adoption. *Internet Research*, 29(3), 578–602

Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. *Computers in Human Behavior*, 25(3), 778–784

Lazar, A., Koehler, C., Tanenbaum, J., & Nguyen, D. H. (2015). *Why we use and abandon smart devices.* Paper presented at the Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing

Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the Technology Acceptance Model. *Computers & Education*, 61, 193–208

Liébana-Cabanillas, F., Marinković, V., & Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *International Journal of Information Management*, 37(2), 14–24

Lu, H. P., & Yang, Y. W. (2014). Toward an understanding of the behavioral intention to use a social networking site: An extension of task-technology fit to social-technology fit. *Computers in Human Behavior*, 34, 323–332

McKinney, V., Yoon, K., & Zahedi, F. M. (2002). The measurement of web-customer satisfaction: An expectation and disconfirmation approach. *Information Systems Research*, 13(3), 296–315

Mettler, T., & Wulf, J. (2019). Physiolytics at the workplace: Affordances and constraints of wearables use from an employee's perspective. *Information Systems Journal*, 29(1), 245–273

Muhammad, S. S., Dey, B. L., & Weerakkody, V. (2018). Analysis of Factors that Influence Customers' Willingness to Leave Big Data Digital Footprints on Social Media: A Systematic Review of Literature. *Information Systems Frontiers*, 20(3), 559–576

Nascimento, B., Oliveira, T., & Tam, C. (2018). Wearable technology: What explains continuance intention in smartwatches? *Journal of Retailing and Consumer Services*, 43, 157–169

Nasir, S., & Yurder, Y. (2015). Consumers' and physicians' perceptions about high tech wearable health products. *Procedia-Social and Behavioral Sciences*, 195, 1261–1267

Nieroda, M. E., Mrad, M., & Solomon, M. R. (2018). How do consumers think about hybrid products? Computer wearables have an identity problem. *Journal of Business Research*, 89, 159–170

Niknejad, N., Ismail, W. B., Mardani, A., Liao, H., & Ghani, I. (2020). A comprehensive overview of smart wearables: The state of the art literature, recent advances, and future challenges. *Engineering Applications of Artificial Intelligence*, 90, 103529

Olsen, S. O., Wilcox, J., & Olsson, U. (2005). Consequences of ambivalence on satisfaction and loyalty. *Psychology & Marketing*, 22(3), 247–269

Pagani, M. (2006). Determinants of adoption of high speed data services in the business market: evidence for a combined technology acceptance model with task technology fit model. *Information & Management*, 43(7), 847–860

Pal, D., Funilkul, S., & Vanijja, V. (2018). The future of smartwatches: assessing the end-users' continuous usage using an extended expectation-confirmation model.Universal Access in the Information Society,1–21

Piccialli, F., di Cola, V. S., Giampaolo, F., & Cuomo, S. (2021). The Role of Artificial Intelligence in Fighting the COVID-19 Pandemic. *Information Systems Frontiers*, 23(6), 1467–1497. https://doi.org/10.1007/s10796-021-10131-x

Pinsonneault, A., & Kraemer, K. (1993). Survey research methodology in management information systems: an assessment. *Journal of management information systems*, 10(2), 75–105

Priyadarshinee, P., Raut, R. D., Jha, M. K., & Gardas, B. B. (2017). Understanding and predicting the determinants of cloud computing adoption: A two staged hybrid SEM-Neural networks approach. *Computers in Human Behavior*, 76, 341–362

Rubin, A., & Ophoff, J. (2018). *Investigating Adoption Factors of Wearable Technology in Health and Fitness.* Paper presented at the 2018 Open Innovations Conference, OI 2018

Sharma, R., Rani, S., & Gupta, D. (2019). Stress detection using machine learning classifiers in internet of things environment. *Journal of Computational and Theoretical Nanoscience*, 16(10), 4214–4219

Shen, X. L., Li, Y. J., & Sun, Y. (2018). Wearable health information systems intermittent discontinuance.Industrial Management & Data Systems

Siponen, M., & Klaavuniemi, T. (2020). Why is the hypothetico-deductive (HD) method in information systems not an HD method? *Information and Organization*, 30(1), 100287

Strong, D. M., Dishaw, M. T., & Bandy, D. B. (2006). Extending task technology fit with computer self-efficacy. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 37(2-3), 96–107

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48(6), 1273–1296

Teo, T. S., & Men, B. (2008). Knowledge portals in Chinese consulting firms: a task–technology fit perspective. *European Journal of Information Systems*, 17(6), 557–574

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 37(1), 21–54

Venkatraman, N. (1989). The concept of fit in strategy research: Toward verbal and statistical correspondence. *Academy of management review*, 14(3), 423–444

Visuri, A., Sarsenbayeva, Z., van Berkel, N., Goncalves, J., Rawassizadeh, R., Kostakos, V., & Ferreira, D. (2017). *Quantifying sources and types of smartwatch usage sessions.* Paper presented at the Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems

Wairimu, J., & Sun, J. (2018). Is Smartwatch Really for Me? An Expectation-Confirmation Perspective. *In Proceedings of the Americas Conference of Information Systems*, Downtown New Orleans, Louisiana, USA

Wang, X., Wong, Y. D., Chen, T., & Yuen, K. F. (2021). Adoption of shopper-facing technologies under social distancing: A conceptualisation and an interplay between task-technology fit and technology trust. *Computers in Human Behavior*, 124, 106900

Wu, & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221–232

Wu, Wu, L. C., & Chang, S. C. (2016). Exploring consumers' intention to accept smartwatch. *Computers in Human Behavior*, 64, 383–392

Xia, F., Ding, F., Li, J., Kong, X., Yang, L. T., & Ma, J. (2014). Phone-2Cloud: Exploiting computation offloading for energy saving on smartphones in mobile cloud computing. *Information Systems Frontiers*, 16, 95–111

Xiao-Liang, S., Yang-Jun, L., & Sun, Y. (2018). Wearable health information systems intermittent discontinuance. *Industrial Management & Data Systems*, 118(3), 506–523

Yadav, R., Sharma, S. K., & Tarhini, A. (2016). A multi-analytical approach to understand and predict the mobile commerce adoption.Journal of enterprise information management

Yu, T. K., & Yu, T. Y. (2010). Modelling the factors that affect individuals' utilisation of online learning systems: An empirical study combining the task technology fit model with the theory of planned behaviour. *British Journal of Educational Technology*, 41(6), 1003–1017

Zadeh, A., Taylor, D., Bertsos, M., Tillman, T., Nosoudi, N., & Bruce, S. (2020). Predicting Sports Injuries with Wearable Technology and Data Analysis. *Information Systems Frontiers*, 23(4), 1023–1037. https://doi.org/10.1007/s10796-020-10018-3