Understanding the Adoption of Quantified Self-Tracking Wearable Devices in the Organization Environment: An Empirical Case Study

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ABSTRACT

Prior research on wearable devices has focused heavily on the consumer market. This study makes a unique empirical contribution to wearables research by extending the knowledge on factors that contribute to the adoption of quantified self-tracking wearable devices in an organizational environment. A wearable acceptance model (WAM) and factors that can influence the individual's decision to adopt quantified self-tracking wearable devices and self-monitoring practices were tested with an online survey of 129 university employees (faculty, administration) and students. Partial least squares path modeling was applied in an analysis to test nine hypotheses to validate the WAM. The factors in the individual context i.e. attitude plays a significant mediating role between the intention to use and the other influential factors of technology, implementation and risk context. The factors of the fashnology (wearability, aesthetic/design), individual (attitude) and risk context (privacy concern) tend to have strong and direct effects on the intention to use the devices, whereas factors of risk context (privacy concern) and technology context (performance expectancy) have a moderate influence on the intention to use through attitude. Organizational facilitating conditions have a significant negative influence on the intention to use. Surprisingly, effort expectancy does not have any effect on attitude.

CCS CONCEPTS

• Management of Computer and Information Systems

KEYWORDS

Quantified Self-tracking wearable devices, Smartwatch, Pedometer, Quantified-self, Activity tracker, Aesthetics, Privacy, Wearability, Fashnology, Technology acceptance

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1 INTRODUCTION

The Quantified Self-tracking wearable devices, such as smartwatches and pedometers, can influence healthy lifestyle behaviors through "Quantified Self" practices, in which individuals engage in the self-tracking of any kind of biological, physical, behavioral, or environmental information, such as continuous data about vital signs (e.g., heart rate, skin temperature) and environmental variables (e.g., movements) [5,82]. Because of the numerous benefits these quantified self-tracking devices and self-practices can have, more and more organizations are extending self-monitoring practices to workplaces or integrating them into corporate wellness programs [33,45]. However, many researchers believe this can have significant social and ethical implications [57,60,64]. For example, round-the-clock anonymous monitoring without consent and the possibility of sophisticated algorithms being used to manipulate the collected biometric and health-related data for purposes other than increasing physical activity and productivity can create privacy concerns and feelings of uncertainty among individuals [56]. Such privacy concerns and feelings of uncertainty may limit the utilization, acceptability, and effectiveness of an intervention program, which could hinder its future development and scale-ups [91]. Furthermore, in organizational use, unlike in recreation, leisure, and sports activities, quantified self-tracking devices are worn i) in everyday social environments where individuals carefully select clothing and jewelry to present themselves in public settings [76] or ii) in harsh, industrial-environment conditions. The question then arises of whether wearability and device aesthetics (i.e., design) have an influence on individuals' decisions to adopt quantified self-monitoring practices through one of the common business models, for example, Here's Your Own Device (HYOD), in which the devices are provided by organizations [88].

Previous research has offered an understanding of the consumer market segment of various device categories, such as smart glasses, watches, or fitness trackers, through different models and theories, such as the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), and the UTAUT2 with additional constructs. However, key issues have yet to be addressed in the scientific literature, for example, the contributing factors that influence an individual's adoption of quantified self-tracking practices through Here's Your Own Device programs. For example, the literature review done by Kalantari [41] revealed that a majority of researchers have utilized the TAM, the UTAUT, UTAUT2, the theory of planned behavior (TPB) framework, the uses and gratifications theory, and the innovation theory for their analyses to understand the adoption of wearable devices in the consumer market segment.

Therefore, in this paper, we utilize an empirical case study to investigate and demonstrate the contributing factors that influence individuals' decisions to adopt quantified self-tracking practices through Here's Your Own Device programs. We focus on a European university, where there are multiple stakeholders, such as students and employee (faculty, administration), and where the concept has not been widely explored. Thus, this paper empirically investigates contributing factors that influence a student, employee (faculty, administration)'s decision through survey on adoption of quantified self-practices through Here's Your Own quantified self-tracking devices with three related research questions: **RQ1:** What specific factors of context can obstruct the adoption of quantified self-tracking devices among employees and students? **Rationale:** Identify the range of variables within the context that influences employees' and students' decision to adopt of quantified self-tracking devices for quantified self practices in the university settings. **RQ2:** How are these factors within the context of use related to one another, to quantified self-tracking devices and to user behavior? **Rationale:** Indicate the extent to which these identified variables are interrelated. **RQ3:** How do the demographic variables of gender and user role (i.e., employees versus students) in the university environment affect the intention to use quantified self-tracking? **Rationale:** Indicate the extent to which group moderation affects the adoption.

To answer these questions, we present a research model that is based on one proposed by [78], which incorporates the well-established UTAUT introduced by [86] and a framework created by [12]. This combined model is referred to in this paper as the wearable acceptance model (WAM) and is validated with the partial least squares path modeling (PLS-PM) method. The outcomes of this study, particularly regarding adoption of quantified self-tracking devices, would be of interest not only to universities, but also to other stakeholders, such as device manufacturers and researchers, in terms of enhancing user experience and creating new marketing and user engagement strategies.

1.1 Prior research and related work

Potnis et al. [72] examined four-year college students' intention to use internet-based safety devices using the UTAUT model and trusting beliefs that are related to the present work. However, their study focused on low-cost personal safety wearables rather than smartwatches and pedometers and only among students. The study presented in this paper expands the view on wearables towards more high-end devices and broader user roles. Similarly, Adapa et al. [3] examined the factors associated with the adoption of smart wearable devices in the university environment among 25 students and working groups. The study presented was qualitative and analyzed through a laddering approach. However, the study mainly evaluated smart glasses and smartwatches and the factors influencing their adoption for daily use rather than the specific purpose of utilization by a university to promote physical well-being or the intention to use.

2 RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

2.1 Research model

Schaper et al. [78] unified the frameworks of [12] and the UTAUT model presented by [86] to present their own model to explain how intention to use is affected by three contexts in the health sector: i) individual (computer anxiety, attitude, and self-efficacy); ii) technological (performance expectancy, effort expectancy); and iii) implementation (social influence, compatibility, and organizational facilitating conditions). [78] empirically validated the model using data from 2,044 survey respondents. The model also incorporated moderating variables to meditate the impact of the three main contexts: age, gender, experience, voluntariness of use, access, clinical specialty, clinical workload, setting type, and geographic area. Schaper et al. [78] model was applied to understand the intention to use quantified self-tracking devices for this research because it utilized the framework provided by [12], which is well accepted in the healthcare sector and validated the UTAUT model presented by [86], which accounts for 70% of the variance (adjusted R^2) in usage intention research. [50] asserted that "subsequent researches tested UTAUT and accepted it as a definitive model that synthesizes the known factors and provides a foundation to guide future research in the area of technology adoption."

In the implementation context, though, previous research on the adoption of technologies found that there is no effect by social influence on attitude or intention to use [12,46,78]. Chau et al. [12] suggested that the insignificance of social influence is due to the individuals' professionalism within the work environment and that management needs to focus on highlighting and demonstrating the technology's usefulness rather than depend heavily on persuasion by those with limited experiences with the technology. Therefore, in the context of this study of the intention to use quantified self-tracking devices in the university environment, social influence was not included as a variable that can affect individual's thoughts, feelings, attitudes, or behaviors [74] while forming intention to use. Similarly, compatibility was dropped, as this factor is mostly perceived by healthcare professionals to be consistent with their practice style or preference [12,78].

Kalantari [41] asserted that "some of the influential factors in the adoption of wearable devices such as privacy issues and aesthetics are more subjective than others and hence arouse arguments that need to be addressed." Earlier studies have established that the devices are defined by their wearability principles; the devices can be of various forms and factors and can be applied in several domains ranging from entertainment to medical and critical safety systems [54,63]. Since wearables are counted as fashnology, which represents consumer perceptions of wearable technologies as a combination of "fashion" and "technology" [76], their characteristics such as wearability and aesthetics (design) will play a large role in the intention to use. [80] referred to aesthetics (design) as the objective features of a product (e.g., color, form, tone, and texture).

According to Garba et al. [27], "Privacy concern is growing about how personal information is exposed by organizations intentionally or as a result of their information systems being hacked." They further pointed out that such concern makes individuals' ability to manage, or trust organizations to manage, their personal information problematic. Therefore, device-specific factors, purpose of use, domains, and privacy concern can be dissuading factors in predicting the intention to use wearable technology in the organizational market segment. While the model presented by [78] has been applied to study technology acceptance, we argue that it is not adequate for studying the determinants of acceptance and use of quantified self-tracking devices in the university environment. It was necessary in this study to include the fashnology and risk contexts.

Therefore, to validate and enhance our understanding of the factors that affect university employees' and students' adoption of quantified self-tracking devices, we modified the factors within [78] model and included the factors pertaining to privacy concern, wearability, and aesthetics (design) to the contexts of risk and fashnology. In so doing, we have proposed a model (see Figure 1 below) with which to measure the variables within the context and compare their influence on current behavioral intention to use wearable devices among university students and employees.

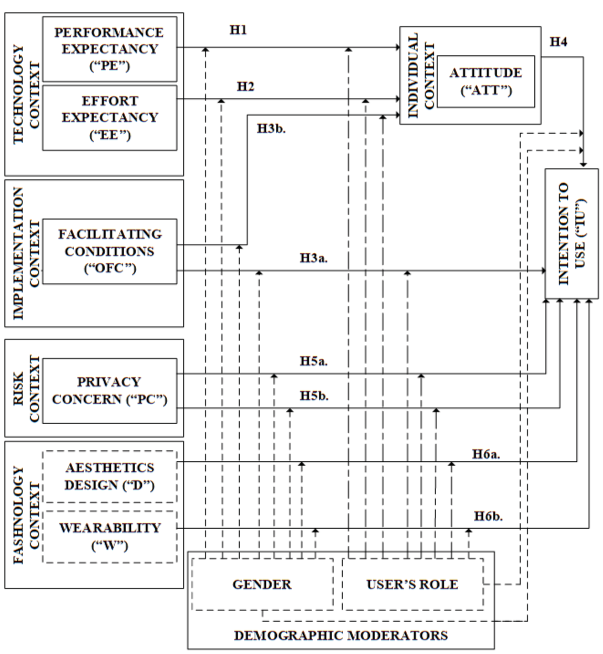

Figure 1: Wearable Acceptance Model (WAM)

However, since all of the previous studies on wearable adoption were conducted on the consumer level, this study also validates how gender and user roles moderate and explain the behavior differentiation on different relationships in the organizational environment [39].

2.2 Technology Context

The technology context comprises two technology determinants: performance expectancy and effort expectancy due to the importance of perception in an individual's acceptance of technology [78]. Performance expectancy is the extent to which the user believes the technology will help them achieve their daily tasks [86]. Performance expectancy affects an individual's attitude to use technology [39,79] and lack of support for this variable's effect on intention warrants further exploratory analysis. In the current context, it refers to the students' and employees' perception that using quantified self-tracking devices can be beneficial (i.e., improve physiological well-being and efficiency, enhance physical activities, and increase productivity) and enjoyable in daily life to perform certain activities without much effort, thus directly affecting the attitude to use the technology. **H1.** Performance expectancy will have a positive effect on the attitude of the university employees' and the students' intention to use. Effort expectancy is defined as the degree of ease associated with the use of the technology [86]. In the context of quantified self-tracking devices, it has been seen that when users feel that wearable devices take up less time and effort to learn and use, they develop an attitude to use the device. **H2.** Effort expectancy will have a positive effect on the attitude of the university employees' and the students' intention to use quantified self tracking wearable devices for quantified self practices.

2.3 Implementation Context

The implementation context refers to the specific professional environment of the user and includes the determinant of organizational facilitating conditions [78].

Organizational facilitating conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology or the perception of external control [86]. It incorporates objective factors in the implementation context, such as management support, training, and the provision of computer support [78]. Mahadeo et al. [59] reported that an absence of facilitating resources may represent an obstacle to use and thus prevent the creation of intention to use. A study by [84] also reported that organizational facilitating conditions affect the intention to use. In this study context, quantified self-tracking devices require connectivity with external devices such as smartphones, and the necessary knowledge to use applications on those external devices or on the quantified self-tracking devices themselves. Although [78] hypothesized that organizational facilitating conditions will not have a significant influence on the intention to use and will only have a positive effect on user behavior, this paper proposes that support from the parties involved will significantly create positive feelings toward the intention to use as well as the attitude of an individual. **H3a.** Organizational facilitating conditions will have a significant influence on the students' and employees' intention to use quantified self-tracking devices. **H3b.** Organizational facilitating conditions will have a positive effect on the attitude of the university employees' and the students' intention to use.

2.4 Individual Context

The individual context refers to an individual's attitude towards technology [15]. Attitude plays important roles in an individual's judgments, evaluations, and behaviors [90] and consist of three dimensions—cognitive, affective, or emotional—along with a conative or behavioral dimension [22]. Despite the importance of attitude towards behavior in Theory of Reasoned Action and Theory of Planned Behavior, the concept of attitude has not always been the focal interest in information systems research on technology acceptance and use [90]. Attitude can be defined as the degree to which a person has a favorable or unfavorable evaluation of the relevant behavior, based on the likelihood that a behavior has particular outcomes, and the evaluation of the importance of these outcomes [38]. Earlier research affirmed that attitude is an essential factor influencing a user's behavioral intention to use a given technology [8,11]. For example, a user who believes that the new technology will be useful and relatively easier to implement may be expected to have a more positive attitude towards that particular technology [10]. To ascertain if attitude affects students' and employees' intention to use quantified self-tracking devices, this study proposed following hypothesis: **H4.** The university employees' and students' positive attitudes towards quantified self-tracking devices create the behavioral intention to use.

2.5 Risk Context

The risk context refers to uncertainty on objectives due to the adverse impacts that would arise if a circumstance or event occurs and the likelihood of occurrence [9]. In the proposed model, the risk context is refined into privacy concern.

In the context of this study, quantified self-tracking devices can be used to collect the health information data of the employees' and students' activities (e.g., heart rate and body temperature, sleeping habits, and number of steps walked daily) to provide individual benefits. However, they can also have adverse effects on privacy at both the individual and societal level [9] if a privacy boundary line is crossed [19] through the profiling of the individuals [37]. On one hand, the collected data can assist involved parties such as the university, the relevant health professionals, third-party service providers, and technology designers in monitoring health and tracking fitness activities, analyzing and detecting early health-related issues, and suggesting specific wellness programs [68]. However, employees' and students' health-related data are not "owned" by the individuals themselves, but are stored by the involved parties, such as the manufacturer who supplies the device [71], health professionals, and third-party service providers. In addition, [71] cautioned that sophisticated algorithms can cross-reference wearable-generated biometric data with "digital traces" from other sources such as social networking sites, which could then be used to predict a user's behavior like personality and risk-taking. Such health-related data and digital traces could easily be leaked, sold, or misused [4]. Lupton [58] asserted that the "privacy and security of people's personal digital data are currently not well protected." Four major dimensions of privacy concern can arise among the students and employees: collection, control, awareness, and access. [25] defined collection as an individual's level of concern about the amount of personal data possessed by others. Control is the ability of individuals to be heard on how personal data is used and, on its access, modification, and deletion. Awareness is an individual's degree of information about the organization's privacy practices. Finally, access is defined as who has access to their private information and how such information will be used [83]. According to earlier literature, privacy concern can engender feelings of apprehension and cause users to form a negative attitude and intention to use. Therefore, we propose the following hypothesis: **H5a.** Privacy concern has a significant influence on the students' and employees' attitude to use quantified self-tracking devices. **H5b.** Privacy concern has a significant influence on the students' and employees' behavioral intention to use quantified self-tracking devices.

2.6 Fashnology Context

The fashnology context refers to the device characteristics and the fashion-related factors of wearable devices, which can affect user perception and intention to use. Motti et al. [66] proposed that wearables come in different forms to be worn on various parts of the body. Baber et al. [6] stated that adding a load to the body in the form of a wearable computer may significantly affect many physical factors. As wearables are in close proximity to the body [81], they must satisfy users' body shapes, sizes, and dimensions, as well as their preferences, interests, and wishes [66]. Gemperle et al. [29] defined wearability as the interaction between the human body and the wearable object. Therefore, wearability plays an important role when it comes to wearable devices, as a wearable should not significantly change the current individual's habits while they use it and should be no different from when an individual wears a costume [32].

With the constant search for new styles, sensations, and experiences [21], individuals are no longer willing to accept a product that does not fit their daily fashion lifestyle. [85] point out that design is increasingly becoming an important strategic tool and a success factor for firms offering personalized consumer durables. Previous studies [1,40,87] addressing aesthetics found that they play a rather important role in the duration of user–wearable device interaction. Results from a study by [80] showed that aesthetics have a stronger influence in the domestic and leisure domains than in the work domain.

Thus, both aesthetics (design) and wearability will act as factors affecting the intention to use the quantified self-tracking devices. With regard to the fashnology context, we make the following hypotheses**: H6a.** Aesthetics/design will have a significant influence on the university employees' and students' intention to use quantified self-tracking devices. **H6b.** Wearability will have a significant influence on the students' and employees' intention to use.

2.7 Moderators

We tested group moderation effects in the research model by gender and the user's role in the organization.

Over the past few years, the gender gap with regards to the adoption of technology has been studied frequently. [53] noted that "males and females do possess different personal traits and societal roles, and these differences are reflected in their perceptions, processing of information, and usage of information technologies such mobile phones, computers, advertising, and the internet." A crucial analysis made by [18] indicated that men are more likely to be highly technologically active or move through the technology adoption model more quickly than their female counterparts. Similarly, [55] found that men are more confident in their ability to master technical skills and are more willing to try new technology products. On the other hand, they found that women took technology functions and designs as more important drivers for their perceptions of usefulness. Based on existing studies [18,53], gender differences are expected to have a moderating effect on the behavioral intention to use quantified self-tracking devices.

Similarly, to compare moderation effects relating to one's social status and life situation, we defined users' roles by their status in the university as either students or employees. On the conceptual level, the student and employee groups have been shown to link the use of wearables in different ways to their personal values, wherein the drivers to use the devices differ [3,16]. The driver to use wearables relates to personal interest amongst the students, whereas the employee groups favor professionalism and supporting social status [3,75]. The student and employee groups have differences in their flexibility regarding the set of factors to assess wearables, which leads to situations in which the employee group's needs are more specific. The rigidity of the technology perceptions among the employees may also be derived from their roles as teachers, which increases the overall need for clarity as an expectation [49]. Therefore, we expected the user's role in the organization to be a moderator.

3 DATA ANALYSIS AND RESULTS

The data was collected as a part of a case study to discover factors that influence the employees' and student's intention to use quantified self-tracking prior to the implementation in order to reduce the risk in early stage of abandonment in a university setting. The university was chosen as a case study because it is a large organization with multiple levels of employees' and student.

3.1 Research Setup and Data collection

To test the hypothesize, we considered an online survey as an instrument of data collection. The measurement items for all constructs involved (see Appendix A) during survey were adapted from the previous studies with modifications. Each item was measured on with seven step Likert scale. The formulated measurements items were examined by the researchers in the product and service innovation, information system field for the verification of its usefulness. The research was performed at a European university in 2017 that teaches engineering and business sciences. Both the employees and the students have an academic background and can be considered experienced in using modern technology, as both work and studies require the use of advanced electronics or software.

They survey was posted at university intranet portal over a period of 10 days where a total of around 6300 students, employees had free access to it. A total of 129 individuals gave their responses. All obtained responses were valid, because all the answers were mandatory, and only students, employees could complete the survey. Data from the survey responses were downloaded from the Webropol online platform into spreadsheet software and were analyzed using the SmartPLS 3.0 statistical data analysis tool.

3.2 Measurement and Model Validity

We applied PLS-PM in the analysis with non-parametric bootstrapping to address the slight non-normality of the observed variables and the somewhat small sample size [31,34]. Indeed, the WAM is relatively complex in terms of the number of structural paths. The PLS-path model was built on 19 measurement items which formed latent factors of two to four observed variables and their hypothesized interactions. The model structure compared to observations in the data requires selection of a method that produces converged and admissible solutions even with small samples. We expect the given model structure has not validity problems compared with the general guideline of the PLS-PM. In addition, the non-normal data can be analyzed with covariance-based structural equation modeling (SEM) with least square methods, but the sample size requirements will be significantly higher for reaching reliable results [23,70]. The complexity of the model, by the estimated parameters, is limited in the covariance-based SEM as well. Of the 129 respondents, 55.8% (n=72) were males and 44.19% (n=57) were females. The respondents were either university faculty or administration (n=55, 42.64%), students (n=51, 39.53%), or both (n=23, 17.83%). The respondents' ages ranged from 18–24 years (n=22, 17.05%); 25–29 (n=53, 41.09%); 30–34 (n=18, 13.95%); 35–39 (n=7, 5.43%); 40–44 (n=6, 4.65%); 45–49 (n=7, 5.43%); 50–54 (n=10, 7.75%); 55–59 (n=3, 2.33%); and 60+ years (n=3, 2.33%).

The measurement model was validated with regard to measurement reliability, validity of the factor structure, and the discriminant validity [28,36]. The measurement reliability was assessed using construct reliability (CR), and the variance was captured by the latent construct by the average variance extracted (AVE) [24]. The CR coefficient should exceed 0.50 to indicate acceptability if the model validity is otherwise good [48,52]. The measurement reliabilities are reported in Table 1. Additionally, complete set of both measurement items and reliabilities are presented in Appendix A. The CRs of the latent constructs varied from 0.844 to 0.924, providing high reliability for further analyses.

The factor structure of the measurement model was analyzed in terms of the significance and weight of the factor loadings, reliability, validity, and for the cross-loadings between latent factors. All the loadings in the outer model (the measurement model) were significant and acceptable, varying from 0.774 to 0.919. The convergent validity of all latent factors in terms of AVE was acceptable, being higher than 0.50 for all the measured concepts [24]. We assessed the discriminant validity of the measurement model through cross-loading the measurement items and by the square root of AVE (the Fornell-Larcker criterion) [28,36] and by the heterotrait-monotrait ratio of the correlations (HTMT) [30]. All measurement items were found to be highly loaded to the defined latent factors, and the cross-loadings were not higher than 0.41. The square roots of the AVE were significantly higher than the correlations between any latent factors, manifesting a good discriminant validity of the measurement model. Finally, the HTMT ratios between the latent constructs were lower than 1, indicating acceptable levels of collinearity.

Table 1: Measurement reliabilities

	Loading	t-value	p-value	Mean	SD	AVE	CR
TECHNOLOGY CONTEXT							
Performance Expectancy (PE)						0.936	0.786
PE1	0,905	39,345	****	4.915	1.510		
PE2	0,916	53,761	****	5.178	1.517		
PE3	0,919	49,614	****	5.070	1.458		
PE4	0,802	20,765	****	4.194	1.676		
Effort Expectancy (EE)						0.877	0.704
EE1	0,774	9,341	****	5.597	1.315		
EE2	0,919	51,956	****	5.155	1.303		
EE3	0,818	13,887	****	5.574	1.402		
IMPLEMENTATION CONTEXT							
Organizational Facilitating Conditions (OFC)						0.844	0.732
OFC1	0.758	5.954	****	5.450	1.575		
OFC2	0.944	26.184	****	5.519	1.398		
INDIVIDUAL CONTEXT							
Attitude (ATT)						0.924	0.802
ATT1	0.879	30,758	****	4.496	1.712		
ATT2	0.887	26,002	****	5.248	1.468		
ATT3	0.919	65.501	****	5.155	1.444		
RISK CONTEXT							
Privacy concern (PC)						0.918	0.849
PC1	0,911	39,532	****	4.736	1.746		
PC2	0,931	64,655	****	4.682	1.716		
FASHNOLOGY CONTEXT							
Aesthetics/Design (D)	1.000	-	-	5.271	1.440	1.000	1.000
Wearability (W)						0.903	0.824
W1	0.914	40.525	****	5.481	1.214		
W2	0.902	32.597	****	5.829	1.128		
Intention to use (IU)						0.921	0.796
IU1	0,872	30,119	****	5.512	1.526		
IU2	0,878	29,635	****	4.767	1.789		
IU3	0,925	47,170	****	5.124	1.671		

n) not significant, *) Statistically significant at $p<0.1$, **) Statistically significant at $p<0.05$, ***) Statistically significant at $p<0.01$, ****) Statistically significant at $p<0.001$|

We analyzed the main effects in the model, defined through hypotheses 1 to 6 (Table 2). In the analysis, the bootstrap sample size was n=129, which is identical to the original sample size. The resampling of the data was repeated 5,000 times in the analysis, which is adequate for the estimation of the model parameters [34,42]. The R^2 for the latent variables in the path model varied from attitude = 0.691 to intention to use = 0.670. The explanatory power of the model is high regardless of a relatively low sample [2,69].

We analyzed the empirical data in three phases to test the set hypotheses of the study. First, the default model with whole data set was analyzed to the test main hypotheses. In the second phase, we tested the group moderation effects using a PLS-multi-group procedure to study the influence of gender and user role on behavioral expectations. In the last phase, we reported the results of the post hoc tests, which assessed the indirect and total effects in the model. In addition, we also tested and validated the quality of the structural model defined by the hypotheses with the following procedure: i) collinearity issues and overall fit, (ii) explanatory power, and iii) path significances. We assessed the collinearity and the model fit to the data to validate the structural model, which provides information on potential misspecification problems. The variance inflation factor of the latent constructs did not indicate collinearity issues, where the values remained clearly below the critical value of 5. To test the hypotheses, we needed to asses overall fit of the structural model to the data to study whether the model was specified correctly. For that purpose, we used the standardized root mean square residual (SRMR; critical value <0.08) and the root mean square residual covariance (RMS_{theta}; critical value <0.12) to specify estimation error and misspecification of the model [31,35]. Here, model fit by SRMR = 0.073 and RMS_{theta}= 0.206 indicates that serious misspecification of the structural model has not occurred. The explanatory power R^2 of the model for endogenous variables was attitude = 0.659 and intention to use = 0.651, which is high regardless of the relatively low sample size [2,73]. Effects sizes f^2 of the exogenous constructs varies from 0.024 to 0.574, small to large, indicating their relevancy in the model.

The default model (see Table 1) shows that attitude has strong and significant positive influence on the intention to use quantified self-tracking devices, which confirms hypothesis H4. The attitude towards wearable technology is influenced by performance expectancy and privacy concern, both of which both have moderate positive influence, confirming hypotheses H1 and H5a. Indeed, the organizational facilitating conditions have significant positive influence on the attitude towards technology, confirming hypothesis H3b. Privacy concern significant positive influence on the intention to use, confirming H5b. In our data, effort expectancy to use technology did not have any effect on the attitude, a rejection of H2. The results show that organizational facilitating conditions (e.g., prior ownership of technology) have a significant negative influence on the intention to use quantified self-tracking devices, rejecting H3a. In the tested model, the appealing design and the quantified self-tracking device characteristics have significant influence on the intention to use, which confirmed hypotheses H6a and H6b.

Table 2 Direct effects in the structural model

Hypothesis	*β*	*T Statistics*	*P Values*
(H1) Performance expectancy will have a positive effect on the attitude of the university employees' and the students' intention to use. (Path: PE →ATT)	.535	8.273	****
(H2) Effort expectancy will have a positive effect on the attitude of the university employees' and the students' intention to use quantified self tracking wearable devices for quantified self practices. (Path: EE → ATT)	.120	1.430	n
(H3a.) Organizational facilitating conditions will have a significant influence on the students' and employees' intention to use quantified self-tracking devices. (Path: OFC → IU)	-.229	2.357	**
(H3b.) Organizational facilitating conditions will have a positive effect on the attitude of the university employees' and the students' intention to use. (Path: OFC → ATT)	.156	1.790	*
(H4) The university employees' and students' positive attitudes towards quantified self-tracking devices create the behavioral intention to use. (Path: ATT → IU)	.541	7,899	****
(H5a.) Privacy concern has a significant influence on the students' and employees' attitude to use quantified self-tracking devices. (Path: PC → ATT)	.250	3.955	****

(H5b.) Privacy concern has a significant influence on the students' and employees' behavioral intention to use quantified self-tracking devices. (Path: PC → IU)	.205	2.435	**
(H6a.) Aesthetics/design will have a significant influence on the university employees' and students' intention to use quantified self-tracking devices. (Path: D → IU)	.133	1.987	**
(H6b.) Wearability will have a significant influence on the students' and employees' intention to use. (Path: W → IU)	.275	3.024	***

n) not significant, *) Statistically significant at p<0.1, **) Statistically significant at p<0.05, ***) Statistically significant at p<0.01, ****) Statistically significant at p<0.001

We tested the group moderation effects of gender (see Table 3) and user role (see Table 4) to assess whether the perceptions about technology use differ among user segments. The multi-group tests were independent from each other. The analysis revealed that the empirical model includes constantly significant paths and some specific moderations by the tested groups.

We found that the influences of attitude on intention to use and of performance expectancy on attitude were always significant paths in the model. However, group moderation was found between the student and employee user groups, where the influence was stronger in the latter mentioned group. Furthermore, the user's role moderated the influence of wearability on the intention to use where the employee user group showed weak positive influence. We found gender differences in the factors explaining both the attitude formation and the intention to use. In the findings regarding the attitude formation between genders, privacy concern had significant positive influence among males only, whereas organizational facilitating conditions had a significant positive influence among females. The influences of privacy concern and wearability on the intention to use were also moderated by gender. Privacy concern had significant influence on the intention to use only among the male users, and the wearability of the device had significant positive influence on intention in the female group only.

Table 3 Group moderation effect, gender differences

	Males			Females			Difference	
Path	β	T	P	β	T	P	D β	p (two-tailed)
PE→ATT	.518	5.560	****	.499	4.936	****	.019	n
EE→ ATT	.164	1.614	n	.128	0.925	n	.036	n
OFC→ IU	.047	0.534	n	-.313	1.668	*	.266	n
OFC→ ATT	.003	0.041	n	.280	2.255	**	.277	**
ATT→ IU	.555	6.630	****	.454	3.670	****	.100	n
PC→ IU	.312	3.166	**	.058	0.401	n	.254	*
PC→ATT	.338	4.655	****	.130	1.207	n	.208	*
D→ IU	.106	1.535	n	.179	1.426	n	.074	n
W→ IU	.104	1.199	n	.446	3.098	***	.342	**

n) not significant, *) Statistically significant at p<0.1, **) Statistically significant at p<0.05, ***) Statistically significant at p<0.01, ****) Statistically significant at p<0.001 |

Table 4 Group moderation effect, user's role

	Students			*Employees*			*Difference*	
Path	β	T	P	β	T	P	D β	p (two-tailed)
PE →ATT	.428	4.990	****	.609	6.088	****	.181	*
EE →ATT	.293	2.431	**	.089	.549	n	.205	n
OFC → IU	-.211	1.494	n	-.194	1.386	n	.018	n
OFC →ATT	.048	.460	n	.217	1.312	n	.169	n
ATT → IU	.470	4.683	****	.632	5.391	****	.161	n
PC →ATT	.264	3.337	****	.186	1.743	*	.078	n
PC → IU	.074	.619	n	.304	2.293	**	.230	n
D → IU	.452	3.393	****	.151	1.792	*	.121	n
W → IU	.154	1.657	*	.033	.474	n	.300	**

n) not significant, *) Statistically significant at p<0.1, **) Statistically significant at p<0.05, ***) Statistically significant at p<0.01, ****) Statistically significant at p<0.001 | attitude (ATT); intention to use (IU); performance expectancy (PE); effort expectancy (EE); organizational facilitating conditions (OFC); privacy concern (PC); aesthetics/design (D); wearability (W)

4 DISCUSSION

The validity analysis of the model with the PLS-PM technique and CR, AVE, and factor cross-loading indicators showed that the model is internally consistent, explained the relationships between the variables. These results indicate that the survey captured the desired latent constructs well and that the presented WAM provides a method to investigate wearable device acceptance in addition to TAM [17], UTAUT [86] and [78] model. The main advantage of the WAM is that it expands on the work performed by previous designers of acceptance models and is customized for wearables. Using a more general acceptance model for wearables would necessitate having to re-customize the model and re-validate it.

In hypothesis testing, we discovered that the factors affecting the individual context (attitude) have a strong effect on the intention to use, which is consistent with the findings reported by [47,67]. The descriptive results from the WAM demonstrate that user experience is a key issue: If the user learns that the device will motivate them to do more physical activities or elicits a positive mindset about the physical activities through user engagement features—such as data, gamification, and content—they are more likely to form a positive attitude towards the use of quantified self-tracking devices and ultimately a greater intention to use those devices. Le Roux et al. [77] also asserted that attitudes are learned through experiences with a product or from information received or acquired from mass media or individuals.

Therefore, technology designers should be designing quantified self-tracking devices that provide better user experiences, leading to more positive opinions from referents so that users actively build a positive attitude towards the intention to use.

In addition, the model demonstrates that the factor pertaining to the risk context (privacy concern) has a moderate positive influence on the attitude of the user, affecting the intention to use quantified self-tracking devices. Tan et al. [83] wrote, "For users with high privacy concern, perceived usefulness has a significant impact on their usage of intention while perceived ease of use does not." Furthermore, the results also indicate that privacy concern has direct influence on the intention to the use the quantified self-tracking devices, which is consistent with the findings of [51]. Hence, giving a sense of i) disassociability (i.e., actively protecting or "blinding" an individual's self-tracking data from exposure); ii) predictability (i.e., informing individuals about how their information is being handled); and iii) accessibility and manageability (i.e., actively giving access and greater control to manage collected health information data) [9] plays an important role in determining the effect of privacy concern on the individual context (attitude) and the intention to use quantified self-tracking devices. Zhang et al. [89] stated, "Affording users control over information release would not only allow users to modify their privacy settings and gain a sense of autonomy, but also help them predict what information might be at risk, thereby reducing the concern level resulting from uncertainty."

Both factors of fashnology (wearability and design) were empirically validated and shown to contribute to an individual's intention to use quantified self-tracking devices. Therefore, technology designers should consider users' surrounding environments and atmosphere [32], work to improve wearability, and have unique designs while creating quantified self-tracking devices. Furthermore, it is clear that a university implementing the technology should provide choices for quantified self-tracking devices to fit an individual's body shape, size, and dimensions as well as their preferred interests and wishes [66]. Zhang et al. [90] stated, "People do not like their choices being taken away from them or their choices being made for them, and they often react in ways that reflect this." Employees and students should be actively involved throughout the implementation process to assist in forming a positive attitude towards intention to use. According to Karsh [43], "Having employees participate during implementation of technology improves commitment, trust, and control while reducing resistance to change and anxiety" and results in "increases in information and knowledge which reduce uncertainty." Morris et al. [65] agreed that "early perceptions can have a lasting impression on individuals' intentions and behavior."

Additionally, this study found that in the test group two demographic factors moderated the intention to use: the user's role at the university and gender, as self-reported on the survey sheet. The analysis evidenced that the employee respondents were more concerned with wearability than the students. As the employee demographic is generally older than the student group, it makes sense that they are more focused on the physical shape of the wearables and their active relationship with them [29]. In contrast, the students were more concerned with aesthetics (design), suggesting the devices are being used for dual purposes, i.e., as fashion accessories and as a motivational tool for physical activities that reflect individual identities, emotions, and aesthetic values [47]. Katz [44] declared, "Many users invest the communication object with myriad personal decorations and personal significance.

In contrast with [7,61], who found in their studies that privacy is the main concern among female respondents, this study found that privacy was not a significant influence among women on their intention to use quantified self-tracking devices. These differences may be due to broader trust towards the university regarding their data. However, male respondents were concerned to a significant degree towards privacy. This study further affirms that aesthetics plays a large role, especially among females, while forming the intention to use, which is in line with the work of [80]. That is because in some demographics and cultures, women tend to perceive technological products as fashion accessories. The findings regarding the female respondents' concern towards aesthetics (design) reinforce a statement from [14]: "But with the advent of well-designed technological products that are now appealing to women, and which have become ultimately wearable, technology has become as conspicuous a statement as fashion itself." As wearables are at a cross-section of different avenues from fashion to sports, a reasonable explanation would be that different consumer segments have different preferences regarding the intention to use. Our findings also confirm earlier ones [18,53] that suggest gender differences still persist within technology adoption but that the gap is closing.

The differences discussed above highlight the need for further investigation by the research community within the areas of user roles (e.g., further disaggregated into sub-groups according to job status) and gender. First, the sources of why male respondents were significantly concerned with regards to privacy while using quantified self-tracking devices in the university environment for "Quantified Self." The findings may help university management develop effective policies to gain the trust of both genders. Further longitudinal study can be done to follow how the university environment affects perception in both user roles and genders and the motivation to use quantified self-tracking devices for well-being. Within this perspective, the concept of situation awareness proposed by [20] could be adopted. Second, to advance knowledge on both the user group and gender intention to use quantified self-tracking devices, future research should seek to understand the impact of age in relation to gender. The Morris et al. [65] model, which is an extension of the TPB, could be used as a base model to understand core relationships for both gender and age in the context of intention to use quantified self-tracking devices in a university environment.

5 CONCLUSION

To answer our research questions, we first created and presented a new model for the acceptance of wearable devices, the WAM, which is based on the more general UTAUT model. It validated the WAM and showed that the novel factors integrated into the model—the fashnology and risk contexts—had a significant effect on the intention to use in this study. Additionally, in order to answer RQ1, the paper explored which factors can obstruct the utilization of quantified self-tracking devices among users and how these factors are related. The hypotheses for the factors were based on the WAM. The empirical results supported most of the tested hypotheses and initially validated the model. The study demonstrated the importance of accounting for aesthetics (design) and wearability while utilizing quantified self-tracking devices in the university environment. Ultimately, the study showed that if a device was expected to work well, had a good design and wearability, and did not raise privacy concerns, users had a positive intention to use it.

In order to answer RQ2, this study explored the relations between factors that are related to the context of use. We confirmed some of the results from previous research that explored relationships between the factors that affect wearable device adoption evaluation with the TAM [47] and the UTAUT [13] regarding effort expectancy and performance expectancy. Furthermore, the results of this study corresponded with the results of the UTAUT; when variables such as performance expectancy and effort expectancy are present, organizational facilitating conditions become non-significant factors for predicting intent to use. The results match previous scientific as well as market research showing that privacy is a significant factor [26,62]. Finally, in order to answer RQ3, we analyzed demographic differences in gender and user role, and found that factors in attitude formation and intention to use were moderated by gender. User role moderated the influence of wearability on the intent to use. This study extends the state of the art by presenting the WAM, which is a novel, validated, and comprehensive acceptance model that has been specifically adapted for quantified self-tracking devices in the organizational market segment and therefore provides value to practitioners intending to apply quantified self-tracking devices to organizational environment and do survey-based research on technology acceptance.

The main limitations of this study were the relatively small and non-random sample size and fewer influential variables, meaning the results cannot be generalized. Nevertheless, this study can be used as a basis to conduct further research on the adoption of quantified self-tracking devices for quantified self practices in university environments.

APPENDIX A: https://doi.org/10.5281/zenodo.2593834

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