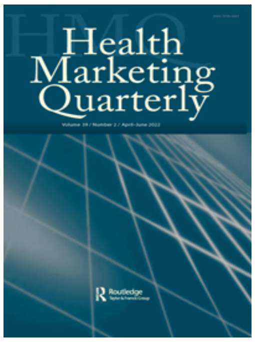

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Factors influencing actual usage of fitness tracking devices: Empirical evidence from the UTAUT model

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ABSTRACT
This research investigates factors influencing the actual usage of wearable fitness devices. Based on the Unified Theory of Acceptance and Use of Technology, the authors propose that privacy concerns, social influence, data accuracy, device engagement, and user efficacy impact the actual usage of wearable fitness devices *via* performance and effort expectancy. Based on 124 responses using the structural equation approach, most hypotheses were supported. The social influence had the strongest indirect effect through performance expectancy, while user efficacy had the strongest indirect effect through effort expectancy. Data accuracy and device engagement had a positive influence on actual usage and privacy concerns negatively affected the device's use.

KEYWORDS
Fitness tracking devices; UTAUT; quantified self; data accuracy; actual usage; privacy; social influence

Introduction

Physical activity is closely linked with health and well-being. The development of wearable technologies has helped people to stay active (Sullivan & Lachman, 2016). A recent research report showed that about one in five United States residents uses a smartwatch or fitness tracker (Vogels, 2020). Many studies have tested the utility of fitness trackers for measuring physical activities and suggest that using these devices facilitates self-regulated health behavior (De Moya & Pallud, 2020). Researchers have also shown an increasing interest in exploring the use of these devices, particularly related to health benefits.

Multiple studies have looked at the positive effect of fitness devices on consumer health. Studies have found the use of calorie trackers has a positive influence on college students' healthy behavior, such as diet restrictions for controlling Body Mass Index (Clark & Driller, 2020; Simpson &

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Mazzeo, 2017). Research also supports long-term and sustainable changes in health and well-being as a result of using fitness tracking devices (Fritz et al., 2014). Another study investigated professional truck drivers' use of wearable devices, who have a high incidence of cardiometabolic risks, to track their activity because of the sedentary nature of their jobs and irregular work schedules (Greenfield et al., 2016) and found that the device improved their well-being.

However, despite the increase in popularity of fitness trackers, there is also scrutiny based on privacy concerns and data accuracy (Esmonde, 2020; Reith et al., 2020). For example, Google's bid to purchase Fitbit raised concerns among privacy and consumer protection groups regarding data aggregation issues in the digital health care sector (Valentina, 2020). In a text analysis of ∼600 Amazon product reviews of six different fitness tracking devices, researchers found that users have concerns about the accuracy and definition of the commonly used measurement metrics (Yang et al., 2015). Perceived data inaccuracies and loss of motivation have also been found to have a strong negative impact on attitude toward using fitness tracking devices (Attig & Franke, 2020). In addition, when the user is not technologically ready, the intention to wear the device reduces (Chiu & Cho, 2020).

In line with these mixed evaluations, recent research and market reports show that many individuals are abandoning fitness tracker devices shortly after adoption (Windasari et al., 2021). Given that the long-term use of these fitness devices influences healthy behavior, it will help the consumers as well as the manufacturers to understand the factors that can encourage the continued use of these devices. In addition, much of the technology acceptance literature focuses on behavioral intentions as the outcome variable of the adoption model (Venkatesh et al., 2003). The relationship between intentions and actual behavior has been held empirically across many contexts (Ajzen, 2012), but this is not always the case. For example, there is often a disconnect between intentions and actual behaviors in green consumption (Nguyen et al., 2019) and information security compliance (Jenkins et al., 2021). Past research has also argued that behavior intention is not necessarily related to the actual usage (Davis et al., 1989; Szajna, 1996). The present study addresses these issues and extends the literature in two ways. First, building and extending the findings of previous research in the wearables domain, we explored several predictors to explain users' actual usage of wearable fitness devices instead of behavioral intentions. Understanding user interactions with fitness tracking devices, and acceptance of the technology in the form of actual usage is particularly important for the development of feature sets in these devices. Second, the study used the theoretical framework of the Unified Theory of Acceptance and Use of Technology (UTAUT) to help understand both the inhibitors as well as facilitators of wearable technology usage. The research question guiding our work is:

What factors impact the actual usage of wearable fitness devices?

We find five factors that play an important role in influencing the actual use of the wearable fitness device: privacy concern, social influence, data accuracy, device engagement, and user efficacy. These five factors also impact the effort and performance expectancy of the device, further resulting in the actual usage.

Theoretical background

The Unified Theory of Acceptance and Use of Technology (UTAUT) is derived from the Technology Acceptance Model, a well-established and vastly used a theoretical model to explore technology adoption. The UTAUT model uses performance expectancy, the degree to which an individual perceives that using a system will help in attaining a gain in the job performance, and effort expectancy, the degree of ease associated with the use of the system, as important predictors of adoption intention (Venkatesh et al., 2003). Scholars have explored the external factors that influence the adoption and usage of technology because they help define different contexts. Venkatesh et al. (2003) suggest exploring new exogenous mechanisms to the core variables of the model (effort and performance expectancy) as a form of extension to gain a deeper understanding of technology adoption.

Qualitative findings have corroborated some of the external factors identified in fitness wearable studies like privacy (Wiesner et al., 2018) and social influence (Reyes-Mercado, 2018) that lead to adoption intentions. But there is little understanding of which external factors affect actual usage of the wearable fitness device. The present study explores the effects of five external variables (privacy concern, social influence, data accuracy, device engagement and, user efficacy) on the performance expectancy and effort expectancy of using a fitness tracking device, and the consequent influence these perceptions have on actual usage of the device.

Hypotheses

Factors influencing performance expectancy

The study explores three antecedents to performance expectancy- privacy concern, social influence and, data accuracy. In the digital era, privacy, defined as freedom from unauthorized intrusion (Merriam-Webster, 2021), relates to the data collected about a user, not known to them. The ubiquity of the internet means that a significant amount of data is collected and shared about the user's behavior when using a website or mobile app. User concerns over the collected data, and the potential of the data to be used by the wearable device company or other companies, might negatively affect a user's perception of the device's performance (Etemad-Sajadi & Gomes Dos Santos, 2020; Wright & Keith, 2014). A study investigating the opportunities and threats of wearable technologies (Saleem et al., 2017) identified the transfer of data from the device to a website or phone as a challenge that is faced in wearable devices. Online transfers were also found to negatively impact privacy and affect the number of transactions in an online environment (Akhter, 2014). Furthermore, the privacy statements provided by the service provider are often written in legal phrasing making it difficult to ascertain where the storage and rights to the data are (Saleem et al., 2017), limiting the ability to make informed decisions. Although wearable fitness devices are intended to improve health and fitness, consumers believe that the type of data collected and shared could be misused by third parties without the explicit consent of the user (Gao et al., 2015; Safavi & Shukur, 2014). Applying the online transaction concept to transfer data from wearable fitness technology, particularly health-related data, users who are concerned with data privacy would further decrease use and therefore not find the device useful.

H1: User's privacy concern will negatively influence users' performance expectancy of wearable fitness devices.

The model explores social influence as the second construct to influence performance expectancy. Social influence is defined as the degree to which an individual perceives the use of technology to enhance their status in their social circle (Moore & Benbasat, 1991). From social cognitive theory, social pressure influences behavior by the perceptions of others (Chang et al., 2016). When a user purchases a device, it can change the perception or attitude of others around him or her. A user might be influenced by others' perceptions and be more likely to accept the technology to please someone else (Wang & Chou, 2016). The influence of the social system is explained through the process of identification, an individual's belief that performing a behavior will elevate their social status within a referent group (Venkatesh & Bala, 2008). In another study, Dholakia et al. (2004) suggested that identification renders an individual to maintain a positive relationship with the group members by motivating him/her to behave similarly. Likewise, in the case of technology adoption, the norms of the social group to which one belongs may influence one's perceptions of the technology. Research on the influence of group membership in buying decisions, specifically for conspicuous goods, has also shown that consumers tend to act in accordance with the group's frame of reference which, in turn, instills belongingness and enhanced self-image among consumers (Childers & Rao, 1992). We expect the psychology of the user to behave in the same pattern when it comes to wearable fitness devices, but in a more enhanced way, because of the visibility of the device. Thus, extending the findings into fitness devices, we hypothesize:

H2: User's social influence will positively influence user's performance expectancy of wearable fitness devices.

The third construct is identified as data accuracy and refers to the trueness and precision of the data provided to the user (Yang et al., 2015). The accuracy of data for metrics, such as activity level, calories burned, amount of time active has a significant effect on a user's perception of the device performance (Gao et al., 2015) A qualitative study that explored end users' motivations to use fitness tracking devices found the numerical feedback, ability to set goals, and data sharing to have a positive effect on continued use of the device (Naglis & Bhatiasevi, 2019). The evaluation of the performance of the technology is dependent on the output that is provided to the user (Bent et al., 2020). The data needs to be current, representative of tasks (e.g., steps or heart rate), and appropriate detail (Kim et al., 2017). Establishing that the user can trust the information they receive is critical for use of technical services that provide health information (Sheng & Simpson, 2015). The interface that displays the information should be consistent and provide essential data for evaluating the use of the technology (Kim et al., 2017). If the accuracy of the data provides useful information to the user, then the user should perceive the technology to perform well and be helpful in accomplishing the desired result. Thus, we posit:

H3: Data accuracy of the wearable fitness devices will positively influence user's performance expectancy for wearable fitness devices.

Factors influencing effort expectancy

This study explores two antecedents to effort expectancy—engagement with the device and user efficacy. Davis et al. (1989) suggest intrinsic motivation, such as engagement with the device, the extent to which the activity of using technology is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated, as a key element to encourage continued use. When the information provided on the wearable fitness device is meaningful and easy to interpret, a user is more likely to take steps to change lifestyle and fitness behavior (Greenfield et al., 2016). Most wearable fitness devices are worn on the arm or used with a mobile app making it easier to continually access and view the data (Wright & Keith, 2014). Many of these devices also have touchscreen-based interactions. Touch interfaces have additional design considerations, and if implemented well, can increase engagement through enjoyment (Yim & Yoo, 2020) and app retention (Shi & Kalyanam, 2018).

Additionally, if a technology is more engaging to the individual it can lead to increased use even if that user has privacy concerns (Pagani & Malacarne, 2017). Other studies have also found an increase in enjoyment which positively affects the likelihood of using wearable technologies and mobile messaging for modifying health behavior (Andrews et al., 2013; Choi & Kim, 2016). The ubiquitousness of technology reduces the perceived effort one puts in using technology (Venkatesh & Bala, 2008). In a similar fashion, we expect that users will have a positive perception about the effort expectancy of the wearable fitness device if the device provides engaging and understandable content to the user. Therefore, we predict that:

H4: User's engagement with wearable fitness devices will positively influence user's effort expectancy.

UTAUT proposes self-efficacy as a form of internal control. Self-efficacy is defined as "[…] an individual difference variable that represents one's belief about his/her ability to perform a specific task" (Venkatesh & Bala, 2008). Social cognitive theory suggests self-efficacy, a form of internal control, to be a key regulatory mechanism that drives human behavior (Bandura, 1977). Adoption of technology literature has often tested the direct relationship between an individual's self-efficacy with technology and intention to adopt (Nysveen et al., 2005). Self-efficacy has been shown to influence a variety of affective and behavioral variables in numerous contexts (Puente-Díaz, 2016). The ability and skills of a user influence the intention to use a technology (Bandura, 1977). For example, users' indirect experience with smartphones is likely to influence the perception of ease of use of a fitness device *via* personal mastery and vicarious experience (Compeau & Higgins, 1995).

Thus, combining the cognitive appraisal theory with UTAUT and with support from past research, we expect that users will have to demonstrate a good amount of self-efficacy to positively perceive the effort exerted to use wearable fitness devices. Thus, we hypothesize that:

H5: User's self-efficacy with wearable fitness devices will positively influence user's effort expectancy.

Role played by performance and effort expectancy for fitness devices

Technology adoption is one of the most established research areas in information systems. More specifically the primary hypotheses of UTAUT have been well validated in the literature since the publication of Venkatesh et al. (2003). Meta-analyses of UTAUT have been conducted across technology types (Khechine et al., 2016) as well as in specific contexts like mobile banking (Jadil et al., 2021) providing strong support for the primary relationships of the theory. Our primary focus is on the external factors unique to the context of wearable fitness devices that affect the perceptions of performance and effort expectancy, along with re-validating the UTAUT model, but in the context of wearable fitness devices. Thus, we hypothesize that the primary effort expectancy and performance expectancy relationships from UTAUT hold in the wearable fitness devices context such that:

H6: User's effort expectancy with wearable fitness devices will positively influence user's performance expectancy.

H7: User's performance expectancy with wearable fitness devices will positively influence actual usage of wearable fitness devices.

H8: User's effort expectancy with wearable fitness devices will positively influence actual usage of wearable fitness devices.

H9: User's performance expectancy mediates the relationship between external factors and actual usage for wearable fitness devices.

H10: User's effort expectancy mediates the relationship between external factors and actual usage for wearable fitness devices.

Methodology

Data collection

The data used in the analysis were collected from a questionnaire distributed electronically to current users of wearable fitness technology. A diverse sample, socio-economically and ethnically, of 124 participants were recruited through Amazon Mechanical Turk (M Turk). We only selected participants who were current users of wearable fitness devices. Thus, the sample was small but a perfect target due to their actual usage experience. Online data collection through M Turk has been suggested as a source for quality data and is intended to reach the desired population (Buhrmester et al., 2011). Therefore, the context of the study, i.e., users of wearable fitness technology, supports the online data collection procedure as appropriate based on users' presumed familiarity with technology. The participants were 58% male and 42% female with 67% between the ages of 30 and 54 years old. Only participants over the age of 18 could participate. Most of the participants were Caucasian (75%), professionals (30%) with a college degree or above (55%); 56% of the sample earned an annual income of $50,000 or above.

Table 1. Mean, standard deviations, and correlations.

	Mean	*SD*	AVE	1	2	3	4	5	6	7	8
1. PE	3.89	0.79	0.68	**0.82**							
2. EE	4.32	0.57	0.68	0.31	**0.82**						
3. Privacy concern	1.98	1.03	0.76	−0.25	−0.27	**0.78**					
4. Social influence	2.75	1.29	0.76	0.50	−0.08	0.14	**0.87**				
5. Data accuracy	4.26	0.64	0.62	0.42	0.80	−0.31	0.14	**0.87**			
6. Device engagement	4.03	0.71	0.68	0.78	0.49	−0.22	0.43	0.62	**0.82**		
7. User efficacy	4.21	0.82	0.69	0.10	0.58	−0.22	−0.18	0.56	0.20	**0.83**	
8. Actual usage*	–	–	0.62	0.41	0.50	−0.24	0.13	0.42	0.42	0.37	**0.78**

PE: performance expectancy; EE: effort expectancy; SD: standard deviation; AVE: average variance extracted; n.a.: not applicable.

The bold numbers on the diagonal are the square root of the AVE. Off-diagonal elements are correlations among constructs.

*Usage was measured by two items indicating the use of wearable technology during the number of hours per day and number of days per week. Therefore, a mean was not calculated, but the items converged well in structural equation modeling.

As members of M Turk, the participants received a monetary incentive to complete the questionnaire. To distinguish the wearable technology (WT) in consumer electronics context to that of medically used devices, the study by Park and Jayaraman (2003), offered examples of 23 WT devices, such as the Fitbit or Apple watch, for participants to choose their model, as well as an option to list other models. None of the participants suggested any confusion regarding the research context of wearable fitness technology. No missing data over 5% were recorded; thus, none of the participants were dropped.

Measurement

Well-established scales were adapted to the context of wearable fitness technology and used to measure the variables of the study. Past research was utilized to adapt the scales for privacy concerns (Chang et al., 2016), self-efficacy (Compeau & Higgins, 1995), data accuracy (Bhattacherjee, 2001), social influence (Kang, 2014), and device engagement (Kang, 2014). Measurement of Performance Expectancy and Effort Expectancy was adopted from measurement constructs developed in related studies (Khalilzadeh et al., 2017) and actual usage items from Venkatesh et al. (2003). Table 1 represents the details of each variable.

Analyses and results

The data were analyzed using two-stage structural equation modeling *via* Lisrel 8.8 and further analyzed *via* bootstrapping with Mplus. First, we established a measurement model followed by an examination of the proposed hypothesized relationships using the theoretical structure model. Mean, standard deviation, and correlations are provided in Table 2.

Table 2. The indicants, measures, and psychometric properties using standardized path coefficients.

	Std. loading	*T*-value*	Std. error	Composite reliability	Average variance
Performance expectancy (items derived from Khalilzadeh et al., 2017)				0.86	0.68
Using WT … improves my performance.	0.82[a]				
… increases my productivity.	0.87	10.88	0.1		
… enhances my effectiveness in life.	0.78	9.43	0.11		
Effort expectancy (items derived from Khalilzadeh et al., 2017)				0.87	0.68
Learning to operate the device is easy for me.	0.81[a]				
My interaction with the device is clear and understandable.	0.88	10.82	0.11		
Overall, I believe the wearable fitness technology is easy to use in my life.	0.79	9.56	0.11		
Data accuracy (items derived from Bhattacherjee, 2001)				0.83	0.62
The data from my device is up to date enough for my purposes.	0.74[a]				
The data maintained by the device is pretty much what I need to carry out my tasks.	0.86	9.04	0.15		
The device maintains data at an appropriate level of detail for my tasks.	0.75	7.96	0.17		
Privacy concern (items derived from Bright et al., 2015; Chang et al., 2016; Hong and Thong, 2013)				0.93	0.76
Are you concerned about your wearable fitness data being shared without your knowledge?	0.93[a]				
Are you concerned that too much personal information is available when you registered the device?	0.91	16.53	0.063		
Are you concerned your wearable fitness can expose you to online identity theft?	0.75	10.94	0.079		
Are you concerned about people you do not know obtaining personal information about you from your wearable device?	0.88	15.19	0.062		
Social influence (items derived from Kang, 2014)				0.86	0.76
Using the device will enhance the image of what others have of me	0.89[a]				
Using the device helps me show others what I am (such as athlete, health conscious, etc.)	0.85	8.51	0.11		
Device engagement (items derived from Kang, 2014 and Venkatesh et al., 2003)				0.87	0.68
Using the wearable fitness device is interesting	0.79[a]				
Using the wearable fitness device is stimulating	0.82	9.74	0.13		
Using the wearable fitness device is meaningful	0.87	10.33	0.12		
User efficacy (items derived from Compeau and Higgins, 1995)				0.82	0.69
I am confident I can use the wearable fitness device if-I had never used one before.	0.87[a]				
I am confident I can use the wearable fitness device if-there was no one around to tell me what to do.	0.79	7.58	0.15		
Actual usage (items derived from Venkatesh et al., 2003)				0.77	0.62
At present, how many hours do you use the wearable technology in a typical day?-daily	0.70[a]				
In a typical 7-day week, how many days do you wear the wearable technology?-weekly	0.87	9.19	0.025		

*p's $\leq$ .05.
[a]Paths set to 1.

Confirmatory factor analysis

The overall fit for the measurement model was $\chi^2 = 257.46$ ($df = 181$; $p \leq .001$); CFI = 0.98; IFI = 0.98; NFI = 0.92; and RMSEA = 0.050; $\chi^2/df = 1.42$ indicating a good fit. The details of the CFA are provided in Table 3. The reliability ranged from 0.77 to 0.93, and the average variances extracted by each construct were >50% (Fornell & Larcker, 1981). Significant standardized loadings of the indicators and composite reliabilities of the latent constructs indicated good convergent validity (see Table 3). Finally, discriminant validity was assessed by examining the squared correlation of the variables to its average variance extracted. All variables exhibited good discriminant validity as explained. If a construct does share some variance with other constructs in the model (Chin, 1998), the square root of AVE should exceed their respective inter-correlations (Farrell, 2010). In our study, none of the inter-correlations exceeds the value of the AVE square root (as shown in Table 2). For example, the average variance explained by effort expectancy (AVEEE = .68) was greater than the shared variance between effort expectancy and performance expectancy (.31) and the values were significant at a p-value of .05 (Anderson & Gerbing, 1991). These results were found to be standard across all the other AVEs and shared variances, thus exhibiting satisfactory discriminant validity.

Structural model: hypotheses testing for the theoretical model

The following results for the structural model show a good fit, as shown in Figure 1: $\chi^2 = 313$ ($df = 191$; $p \leq .001$); CFI = 0.96; IFI = 0.96; NFI = 0.91; RMSEA = 0.066; and $\chi^2/df = 1.62$. The paths proposing a negative relationship from Privacy Concern to Performance Expectancy (H1) and positive relationship from Social Influence (H2) and Data Accuracy (H3) to Performance Expectancy were supported. User Efficacy (H4) and Device Engagement (H5) were found to positively influence Effort Expectancy. Interestingly, the robust link from Effort Expectancy to Performance Expectancy was not significant, not supporting the previous literature. Finally, as proposed, Performance Expectancy (H7) and Effort Expectancy (H8) had a significant positive influence on Actual Usage.

The strongest direct effects were those of Self Efficacy on Effort Expectancy ($\beta = 0.59$) and of Social Influence on Performance Expectancy ($\beta = 0.54$). Device Engagement on Effort Expectancy ($\beta = 0.40$) and Effort Expectancy on Actual Usage ($\beta = 0.41$) had similar effects. The strongest indirect effect was of Self Efficacy to Actual Usage through Effort Expectancy ($\beta_{13}{}^{*}\beta_{38} = 0.24$).

Table 3. Test of the proposed main effect relationships.

Relationship		Dependent variable								
		Performance expectancy ($n = 124$)			Effort expectancy ($n = 124$)			Actual usage ($n = 124$)		
Effect of external factors on mediators		Coeff	LLCI	ULCI	Coeff	LLCI	ULCI	Coeff	LLCI	ULCI
Privacy concern → Performance expectancy	H1	−0.232	−0.405	−0.047						
Social influence → Performance expectancy	H2	0.533	0.363	0.732						
Data accuracy → Performance expectancy	H3	0.33	0.128	0.567						
Device engagement → Effort expectancy	H4				0.473	0.297	0.644			
User efficacy → Effort expectancy	H5				0.220	0.048	0.357			
Effect of mediators on dependent variable (DV)										
Performance expectancy → Actual usage	H7							0.480	0.296	0.649
Effort expectancy → Actual usage	H8							0.274	0.095	0.429
Variance explained (R^2)		49.6% (S.E. = 0.123, $p < .01$)			32.1% (S.E. = 0.096, $p < .01$)			37.4% (S.E. = 0.088, $p < .01$)		

Coeff: regression coefficient; SE: standard error of the coefficient estimate; all coefficient estimates standardized; LLCI: lower bound 95% confidence interval estimate; ULCI: upper bound 95% confidence interval.

The empty boxes are not applicable to the respective rows.

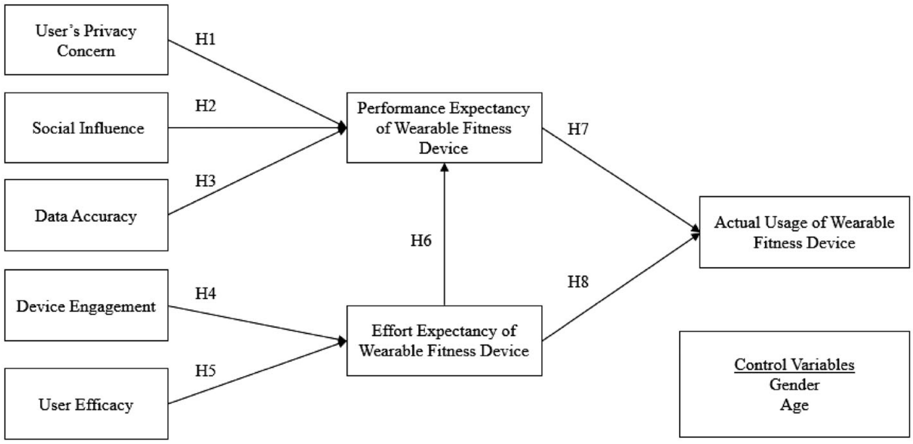

Figure 1. The proposed theoretical model of actual usage of wearable fitness devices.

Main effects with bootstrapping

Further as a robustness check, due to the small sample size, we also ran the same model using the bootstrapping method in Mplus. Specifically, we ran the ML estimation method with 10,000 bootstrap samples as recommended by Shrout and Bolger (2002). The bootstrapping bias-corrected confidence interval procedure along with regression analysis was used to test the hypotheses. The results did not change, and we still found significance as expected. Specifically, bootstrapping with 10,000 samples provided the effects and 95% confidence intervals, we found that Privacy Concern has a significant negative influence on Performance Expectancy (β = −0.232, CI [−0.405, −0.047]), supporting H1, Social Influence has a significant positive influence on Performance Expectancy, supporting H2 (β = 0.533, CI [0.363, 0.732]). Further, Data Accuracy also positively affects Performance Expectancy, supporting H3 (β = 0.330, CI [0.128, 0.567]). Device Engagement was found to positively impact Effort Expectancy (β = 0.473, CI [0.297, 0.644]), supporting H4 along with Self Efficacy, supporting H5 (β = 0.220, CI [0.048, 0.357]). Performance Expectancy positively influences Actual Usage, supporting H7 (β = 0.480, CI [0.295, 0.649]) and Effort Expectancy positively supports Actual Usage, supporting H8 (β = 0.274, CI [0.095, 0.429]). Overall, running SEM as well as bootstrapping yield the exact same results, thus supporting all our hypotheses for main effects, except the direct effect of Effort Expectancy on Performance Expectancy. These details are portrayed in Table 3.

Mediation effects via bootstrapping

Based on the recommendation of Shrout and Bolger (2002), we also tested for indirect effects using bootstrapping analyses (with 10,000 bootstrap

Table 4. Indirect effects of external factors on actual usage *via* performance expectancy and effort expectancy.

			Impact on actual usage		
Independent variable	Dependent variable	Mediator(s)	LLCI	Estimate	ULCI
Privacy concern	Actual usage	Performance expectancy	−0.11	−0.218	−0.035
Social influence	Actual usage	Performance expectancy	0.256	0.146	0.427
Data accuracy	Actual usage	Performance expectancy	0.159	0.058	0.322
Device engagement	Actual usage	Effort expectancy	0.129	0.054	0.227
User efficacy	Actual usage	Effort expectancy	0.060	0.011	0.133

Estimate: indirect effect estimate (unstandardized); LLCI: lower bound 95% confidence interval estimate; ULCI: upper-bound 95% confidence interval estimate.
Total indirect effect = 0.085 0.238 0.272.
Total direct effect = 0.363 0.529 0.596.

samples). Further, as per the bootstrapping procedures described by Hayes (2013), we ran two different mediation models, one for the Performance Expectancy and another one for Effort Expectancy, using 10,000 bootstrap samples for bias-corrected bootstrap confidence intervals. All reported *p*-values are two-tailed. Examination of mediating effects using bootstrapping shows that Performance Expectancy mediates the relationship between Privacy Concern and Actual Usage of a fitness device with a significant indirect effect ($\beta = -0.11$, CI [−0.218, −0.035]), Social Influence ($\beta = 0.256$, CI [0.146, 0.427]) and Actual Usage with a significant indirect effect along with a significant mediation with Data Accuracy variable as well ($\beta = 0.159$, CI [0.058, 0.322]). Similarly, when running the mediation with 10,000 bootstrapping samples for Effort Expectancy as the mediator, we found that Effort Expectancy mediates the relationship between Device Engagement and Actual Usage ($\beta = 0.129$, CI [0.054, 0.227]) as well as between Self Efficacy and Actual Usage with a significant indirect effect ($\beta = 0.060$, CI [0.011, 0.133]). Thus, using bootstrapping at 10,000 samples, we found mediation support for both hypotheses, H9 and H10.

Accounting for the variances, the Performance Expectancy had an R^2 value of 0.496 (S.E. = 0.123, $p < .01$), whereas, the Device Engagement and Self Efficacy variables accounted for 32.1% of the variance for Effort Expectancy (S.E. = 0.096, $p < .01$). Further, Performance and Effort together accounted for 37.4% of the variance for actual usage (S.E. = 0.088, $p < .01$), based on the respective R Squared values. Table 4 reports the details of the mediation effects.

Discussion and implications

The focus of this research is to understand what factors influence both performance expectancy and effort expectancy of a fitness tracking device and its influence on the actual usage of the device. In this context, the empirical results show that device users who were less concerned with data privacy

(H1) perceived the device to perform as per their expectations than those who were more concerned with data privacy. This aligns with findings that trust in connected health technologies affects perceptions of service quality (Etemad-Sajadi & Gomes Dos Santos, 2020). In an age of digital data, wearable devices carry significant personal data about a user's activities. Newer wearable fitness devices have more processing power (e.g., Apple Watch Series 6), and thus more data storage, which could lead to even more privacy concerns. Additional authentication controls on a device could ensure a user's data privacy, but to add authentication, additional logins, passwords, or access codes might be needed. In a small screen environment, a second login can be deemed as cumbersome. Therefore, device size could be a secondary influence on performance, and thus, privacy. Many fitness devices outsource privacy measures to other companies; in these instances, the company performing these extra steps should inform users about privacy measures they are taking, to reconfirm the confidence of those concerned and increase the performance expectancy.

Social influence (H2), change in a user's behavior to enhance social status, and data accuracy (H3), to the user, was found to significantly influence performance expectancy. A wearable fitness device, most often worn on the arm and visible to others, maybe a signal to others that the user is focused on health and fitness. Once others know that the user is committed to health and fitness, this can further influence the user's perception of the performance of the device and encourage continued use. As more wearable fitness devices enter the market, there is a desire to have them look fashionable (Choi & Kim, 2016). The fashionability of the device may further affect social influence and therefore affect performance perception. Thus, manufacturers promoting this device can focus on the social aspect of how one is perceived when they wear the device. Such promotional material can improve the performance expectancy of the device thus benefiting the firm with more sales.

Data accuracy of these devices also improves performance expectancy. The information displayed on the device can allow the user to change their goals, e.g., increasing steps or mileage a day, or changing activity type, such as from walking or running, updating the information creating a useful display (Zhang & Rau, 2015). Typical wearable fitness devices have minimal buttons, use icons with some text representing the data, and use colors for heart rate or steps. Having a small space to display health and fitness information requires that the data be displayed efficiently as well as be informative at a quick glance. In addition, engineers and designers of wearable devices need to consider how the user can customize their data easily to show meaningful patterns to improve the performance expectancy further, and can also prioritize the data they want to see, as not all can be demonstrated because of a small display of the device.

The research results also support a positively significant influence of device engagement (H4) and self-efficacy (H5) on the effort expectancy of the device. Most consumer wearable devices are focused on health and fitness, and users find the devices easy to use if they engage in their goals for health and fitness. Engaging data positively influences the user's perception of effort. For example, using more efficient ways for users to share their daily achievements of fitness on social media increases their motivation as well as their engagement, thus resulting in better effort expectancy. Therefore, device developers can make these engagement options more prominent and remind users of such options, like social media sharing or inviting friends to join in their health goals. Such device engagement can increase effort expectancy.

Additionally, users' belief in their skills and ability to use a wearable fitness device positively influenced effort expectancy. Because the participants were expected to have used a wearable fitness device, users had experience with the technology. This experience most likely increased their confidence (efficacy) related to the effort needed to use the device. After a user buys the device, they gain experience after becoming accustomed to the technology; users can increase their confidence with the device, and thus the effort expectancy, is by frequently viewing the "how to" videos. Additionally, promoting the user-friendly aspect of the device would also be a strategic positioning to increase the user's confidence and improve the effort expectancy. Device manufacturers should re-consider the frequent updates to the device and frequent changes to the layout display as those factors can reduce the confidence in usage.

Interestingly, there was not a significant, positive influence of effort expectancy on performance expectancy (H6) found in past research. This may be related to the user's comfort with many other technological devices, such as smartphones, tablets, and even touch screen appliances. As technology has been incorporated into other commonly used devices and appliances, users have become accustomed to how to use them and do not consider it as a moderating factor for performance expectancy with the ever-changing digital era.

Both performance and effort expectancy (H7 and H8) had a significant positive influence on actual usage. Performance expectancy of the device affects users' perception of its productivity and hence, actual usage. Effort expectancy needed to use the wearable fitness device affects the user interaction with the device. If the user perceives the device as being easy to operate and understandable, they are more likely to use the device. Further, these perceptions mediate the external factors-actual usage relationship. All five external factors (user efficacy, device engagement, data accuracy, social influence, and privacy concerns) affect the actual usage of the wearable fitness device *via* the mediators—performance and effort expectancy.

Our model confirms, by analyzing the actual usage of the wearable fitness device what earlier behavioral intentions research suggested, that there may not be a large purchase intention-actual behavior gap when it comes to wearables adoption as compared to other behaviors like security compliance (Jenkins et al., 2021) and green consumption (Nguyen et al., 2019). These results are also useful to device developers as it highlights not just what consumers say they want, but the features and design elements that are driving their current actual usage behavior. Understanding the features that lead to higher levels of actual use indicates where developers should spend their time on feature sets for the device and decision-making on policies related to privacy and security for a given wearable device.

Limitations and future research

We acknowledge that our study did not come without limitations. The participants for this study needed to have used a wearable fitness device, therefore, one limitation of the research is not investigating a new user's use and experience with wearable fitness devices. Future researchers could use an experimental research design to determine the level of confidence with novice users *vs.* those with either device experience. Another option would be to investigate length of use experience or expand the time horizon to understand wearable technology use from a continuance lens (Bhattacherjee, 2001); this could start from intention of purchase to actual purchase and then, continuous usage, rather than the adoption-based usage we posit in this paper. In addition, understanding how the wearable fitness device looks, such as fashionability, can influence the performance and effort expectancy, and ultimately the use of the wearable fitness device, are good candidates for future research. Comparing different types and brands of wearable fitness devices and how brand perception can impact actual usage would be another avenue for future research.

Finally, the outbreak of COVID-19 has significantly changed the work environment with the majority of employees working from home; lifestyles have changed, encouraging people to seek more leisure activities like hiking and biking as well as camping and backpacking. Future research questions could determine how the wearable fitness device industry is affected by this trend in work-from-home and whether the change affects the actual usage of devices.

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