An acceptance model for sports technologies: the effects of sports motivation, sports type, and context-aware characteristics

Purpose: This study explores the drivers behind sports technology use and identifies the need for a new conceptualization of sports technology adoption. To address this issue, we create a new construct, "context-awareness," with four dimensions: tracking, coaching, sharing, and gamification.

Design/methodology/approach: The paper uses a mixed-method approach, including in-depth interviews and partial least squares structural equation modeling. The proposed model combines technology acceptance frameworks with the Sports Motivation Scale and a novel context-awareness scale. It is empirically tested with a diverse sample of 600 respondents to identify use-intention differences according to sports motivation and sport types.

Findings: The paper reveals group differences in sports type (dynamic vs. non-dynamic) and sports motivation (intrinsic vs. extrinsic) regarding sports technology use. It also suggests that perceived technology characteristics mediate the relationship between context-aware features and intention to use.

Originality: This research introduces a new construct of "context-awareness" into the literature on new technology acceptance. The proposed model combines insights from information systems, sports science, sports marketing, and sports medicine to explain the adoption of complex technology.

Keywords: Wearables, Sports motivation, Sports type, Unified theory of acceptance and use of technology (UTAUT2), Partial least squares structural equation modeling (PLS-SEM), Gamification, Coaching

Paper type: Research paper

Introduction

Recent technological advancements enable sports technologies to track activity, provide feedback, and motivate users (Novatchkov and Baca, 2013). Sports technologies are now ubiquitous and hyper-connected; besides monitoring important body measures, they use artificial intelligence to give feedback and make activity-related suggestions using collected data (Baca *et al.*, 2010; Lee *et al.*, 2016), allow instant sharing of activities, and employ gamification elements (Apple, 2018a). They can also identify the user's location and objective based on previous data and then interpret the user's activity. Essentially, sports technologies exhibit context-awareness characteristics (Dix *et al.*, 2004).

Although sports technologies are widely adopted, their effective long-term use and adoption face ongoing challenges. The COVID-19 outbreak has increased sports wearable sales, but pre-pandemic figures indicate that fitness tracker sales fell 18% in 2017, some 23% below their peak in 2016 (Shirer, 2018; Lamkin, 2018). One market leader, Fitbit, continues to lose active users, reporting a 31% decrease in year-on-year unit sales in 2020 (Fruhlinger, 2018; Curry, 2021). The International Data Corporation (IDC) recently attributed slowing growth to huge adoption in the market. They even reported a decline in certain products such as smart wristbands: worldwide shipments of smart wristbands declined in Q1 2021 by 17.8%, despite the pandemic positively affecting the overall wearables market (Needham, 2021). Therefore, further investigation is necessary to identify what factors influence sports technology adoption.

In this study, the "sports technology" concept encompasses smartwatches that can be used to monitor athletic activities (e.g., Apple Watch, Samsung Gear, and Garmin Fenix), smart wristbands (e.g., Fitbit, Samsung Gear Fit, and Huawei Fit), other sports technology devices mounted to equipment (e.g., bike and dive computers), other wearable technologies and mobile applications for sports activities (e.g., Nike +, Strava, Dietetic, and Argus).

Relevant sports science literature focuses mainly on the relationship between sports technologies and motivation (Lyons and Swartz, 2017; Segar, 2017), sports application acceptance (Kang *et al.*, 2015; Kim *et al.*, 2017), whereas information systems literature uses existing frameworks to explain the adoption and diffusion of these technologies (Canhoto and Arp, 2017; Kim and Shin, 2016; Kim and Chiu, 2019; Lunney *et al.*, 2016; Wu *et al.*, 2016).

Although product-related variables (such as product superiority, relative advantage, newness, and customization degree) have been studied in innovation diffusion research (Goodhue, 1995; Harmancioglu *et al.*, 2009), a gap remains concerning the conceptualization of the acceptance of new sports technologies. Advancements in artificial intelligence and microsensors enable sports technologies to become extraordinarily user-oriented and dynamic. Sports technologies utilize contextual data about users, including their location, heart rate and speed. Sports technologies are, thus, context-aware. Yet, the current literature on their acceptance fails to incorporate product-related variables. In the study domain of sports technologies, we seek to expand knowledge to include the consumer's perspective and the intentions behind their use of context-aware technology. Accordingly, we propose a new construct—context-awareness—of four dimensions: tracking, coaching, sharing, and gamification. This construct reveals the characteristics of new products that influence technology adoption.

This study's primary purpose is to explain how sports technologies' context-awareness characteristics and perceived innovation characteristics affect users' adoption. The study further extends the expanded unified theory of acceptance and use of technology (UTAUT2) (Venkatesh *et al.*, 2012) with new exogenous mechanisms to elucidate existing endogenous constructs in the model. Of particular interest is whether sports type (Mitchell *et al.*, 2005) moderates sports technology use—a relationship yet to be addressed in the literature. Moreover, this study explores the influence of motivation (Pelletier *et al.*, 2013) on sports technology use. While previous studies explain how sports technology usage influences motivation (Segar, 2017), this study investigates the opposite direction: how motivation to participate in sports affects sports technology use. We introduce the new construct of context-awareness into the literature on new technology acceptance. To the best of our knowledge, this study's model is the first to combine academic literature on information systems, sports science, sports marketing, and sports medicine to explain the adoption of complex technology.

Literature review

Adoption and diffusion

Following Rogers's presentation of a generalized diffusion model in 1962, marketing scholars' interest in innovation diffusion escalated after Bass (1969) proposed a growth model for consumer durables. Similarly, interest in information systems rose after Davis (1989) introduced his technology acceptance model (TAM). Referring to consumers' use of innovation, Rogers (1962) used the term "adoption" whereas Davis (1989) coined the term "acceptance": both terms prevail in the literature.

Moore and Benbasat (1991) designed an instrument to measure users' perceptions of innovation based on the characteristics specified by Rogers (1962): relative advantage, compatibility, complexity, trialability, and observability. They added two additional elements: image and voluntariness of use.

Scholars have extended the original TAM with various external variables, including the perceived health-related outcomes of sports technologies (Lunney *et al.*, 2016), users' technology readiness (Kim and Chiu, 2019), and other psychological determinants such as affective quality, mobility, and availability (Kim and Shin, 2016). Choi and Kim (2016) extended the TAM to smartwatches with two non-utilitarian factors: vanity and the desire to be unique; they evaluated the smartwatch as not only an information technology innovation but also a fashion statement.

Venkatesh and colleagues attempted to unify the theories in various diffusion and acceptance studies. They framed the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003), which integrates the essential components of eight well-known models. The performance expectancy, effort expectancy, social influence, and facilitating conditions in the UTAUT model are relatively analogous to the TAM in that external variables influence behavioral intention. In 2012, Venkatesh *et al.* proposed the UTAUT2 model to adapt to the changing technological features of innovations. It adds three more influential variables to the foundation of the original model: hedonic motivation, price value, and habit. Several studies have applied various UTAUT model constructs to explain the adoption of sports technologies (Kang *et al.*, 2015; Kim *et al.*, 2017). An earlier model of sports-related behavior derived from the TAM is the "Sports Website Acceptance Model (SWAM)" proposed by Hur *et al.* (2007). SWAM focused on fans' perception of their sports teams' websites. Wu *et al.* (2016) used a combination of the TAM, innovation diffusion theory, and the UTAUT to explain smartwatch adoption. Reyes-Mercado (2018) used the UTAUT model to compare the behaviors of adopters and non-adopters of wearables, while Yuan *et al.* (2015) used hedonic motivation, price, and habit from the UTAUT2 model to explain intention to use health and fitness apps. In a similar theoretical approach, Barbosa *et al.* (2021) utilized UTAUT2 to predict the intention to use fitness center apps. Cheng et al. (2021) focused on continued usage intention for running apps by using some of the variables from the acceptance model. Other studies have used non-technological variables such as health consciousness (Damberg, 2021) as additions to the UTAUT2 model. In their qualitative research, Canhoto and Arp (2017) studied how the context, users, and device characteristics affect the adoption and continued use of sports technologies. For example, whereas collecting activity data is crucial for adoption, portability is essential for continued use.

This study implements the UTAUT2 as a basic theoretical framework to examine user acceptance of sports technologies. The following hypotheses will be confirmed if sports technology adoption can be explained through the UTAUT2 framework:

H1. Performance expectancy (a), effort expectancy (b), social influence (c), hedonic motivation (d), and habit (e) positively affect behavioral intention to use sports technologies.

The price value variable in the UTAUT2 model is dropped from this study because the sports technologies considered include both free and paid-for devices and apps. The literature suggests that compatibility and facilitating conditions are more suitable for explaining technology adoption at the company level (Venkatesh *et al.*, 2012). Moreover, compatibility is not a significant antecedent of intention to use smartwatches (Wu *et al.*, 2016). Therefore, for the sake of parsimony, we also remove facilitating conditions from our model.

Motivation to participate in sports

Motivation to participate in or quit a sport has been extensively researched (Pelletier *et al.*, 1995; Pelletier *et al.*, 2013). Studies of motivation have been founded on self-determination theory (SDT) (Ryan and Deci, 2000). SDT posits that competence, autonomy, and relatedness are inherent psychological needs: when fulfilled, they generate improved self-motivation and mental health; when unsatisfied, they lead to weakened motivation and well-being. Pelletier *et al.* (1995) adapted SDT to the sports environment by creating the Sports Motivation Scale (SMS). They later collaborated with the scholars who originally formulated SDT to propose an improved scale, SMS II (Pelletier *et al.*, 2013).

However, motivation has attracted limited academic attention in fitness app research. Liu and Avello's (2021) bibliometric analysis revealed that motivation is a keyword in only 1.7% of fitness app-related studies. Segar (2017) argued that fitness trackers are insufficient to sustain motivation when used alone. She added that they might even reduce motivation as sports can become a chore rather than fun. Lyons and Swartz (2017) presented caution against the exclusive use of sports technologies for motivation. They strongly endorsed supporting the use of sports technology with other interventions. They suggested that different sports technologies are suited to different lifestyles and personalities. Villalobos-Zúñiga and Cherubini (2020) also used SDT to study motivation in the fitness apps domain. They adopted the basic psychological needs (BPN) of autonomy, relatedness, and competence (Ryan and Deci, 2017) to code fitness apps. They further coded app features in terms of their support for BPN attributes: reminders and motivational messages are autonomy-supportive features; activity feedback and awards are competence-supportive features; performance sharing and peer challenging are relatedness-supportive features.

In a relatively similar theoretical approach, Molina and Myrick (2021) used SDT as the base theory and found six themes for sustained use of fitness apps: feeling accomplished, stress relief, energy and health, appearance, modeling of behavior, and competition and self-challenge. In line with these findings, motivation to participate in sports is a moderating variable in our research model.

Sports classification

There are several classifications of sports based on empirical data, such as team/individual and indoor/outdoor sports. A broader, systematic classification based on cardiovascular activity was developed by Mitchell *et al.* (2005), who propose nine clusters of sports activities based on dynamic and static components. For the sake of parsimony, we simplify their nine clusters into two: dynamic and non-dynamic sports. Sports that require more cardiovascular activity, such as soccer, basketball, and running, fall into the dynamic category, while yoga, Pilates, and golf fall into the non-dynamic category. To our knowledge, no previous study has examined how sports type affects sports technology adoption.

In addition to the theoretical relationships between primary constructs, each direct effect is tested for moderation by sports type for a more detailed assessment of adoption behavior.

Context-awareness instrument development

Qualitative study

This study’s in-depth interviews were conducted in two stages. Three sports professionals (one female, two males; age 25–45) were interviewed to obtain expert opinions in the first stage. We interviewed a broader selective sample of 12 people (seven females, five males; age 18–35) who regularly participate in sports activities in the second stage.

Of the three professional interviewees, one was an experienced Pilates instructor, the second a certified CrossFit trainer, and the other a fitness trainer and instructor. The average interview duration was 45 minutes. The expert-opinion interviews were mainly intended to confirm the research rationale; hence, the approach was inductive.

For the second-phase interviews, individuals who had actively performed sports activities for at least 1 hour a week for over 1 year and used at least one sports technology were recruited through selective sampling. Interview questions were designed to enable respondents to speak openly, offer opinions, and develop new topics around the subject matter. We employed guided questions to obtain interpretations rather than direct information. Although the questions were specific, we changed them slightly according to the direction of each interview to deepen the conversation and probe for clarification.

All conversations were audio-recorded, and meaningful passages from the recordings and interviewers' notes were subsequently transcribed. Refined transcriptions were descriptively coded. For example, we coded the following comments by an amateur triathlete as *tracking performance*: "Without data, how can I measure my performance? That is why I need this gear for my athletic activities. Sometimes, if I forget to wear my smartwatch, I skip my sports."

After coding the texts, we grouped the codes and created categories. The interviews provided valuable insights on sports technology experiences, opinions, and expectations.

Context-aware instruments

Context-awareness can be defined as the understanding of where (location identification), when (time-awareness), what (perception and interpretation of human activity), and why people are engaging in a particular activity (Dix *et al.*, 2004). The qualitative study and extant literature helped us identify and define four dimensions of context-awareness by which sports technologies can be assessed: tracking, coaching, sharing, and gamification. These attributes are not mutually exclusive; one sports technology may possess multiple elements. Indeed, technological advancements encourage the extensive use of all four.

We created 17 rating scale items to measure context-awareness capacities and enhance understanding of what drives sports technology use. Independent judges assessed content adequacy, while the validity and reliability of items were evaluated based on related literature (Churchill, 1979; Hinkin *et al.*, 1997). We recruited 257 students to test construct validity and reliability and purify the scale items. As recommended by Churchill (1979), we collected two samples: one student sample (n=257) and one study sample (N=600). We surveyed seven academic experts in marketing, economics, and information systems to evaluate the four context-awareness characteristics. We asked them to use their judgment to assign each survey item to the most suitable of the four characteristics. One item with a high conflict rate (60%) was dropped from the study. For all others, at least six of the seven judges agreed that our proposed classifications were applicable, with an average agreement of 90%. Thus, 16 survey items remained for measuring context-awareness characteristics.

The survey items used for each context-awareness characteristic are listed in Table I. The judges verified the face validity of all items. Exploratory factor analysis was conducted to calculate the validity scores of items and constructs. Table II presents the correlated uniqueness measures (Campbell and Fiske, 1959) assessing the discriminant validity of the context-awareness characteristics. All cross-correlations (shown beneath the diagonal) are below .07, indicating no significant shared variance between the factors (Hair *et al.*, 2010). As shown on the right of the table, the average factor loadings (path coefficients) are high for each context-awareness characteristic, indicating excellent convergent validity (Liaukonyte *et al.*, 2014).

[Table I about here]

Last, we checked the reliability of each context-awareness characteristic using Cronbach's alpha, which indicates the consistency of errors and variance in a single factor. A Cronbach's alpha above 0.7 confirms that a construct is sufficiently reliable, and a higher score indicates greater reliability (Hair *et al.*, 2010; Gaskin, 2018). Reliability scores for each context-awareness factor are presented in Table II.

[Table II about here]

Context-awareness tracking

Sports technologies use context-awareness computing mainly to collect data on an individual's location, heart rate, pace, and speed. Some other technologies collect sport-specific data: for example, cyclists require their speed and cadence data.

Hence, we define context-awareness tracking as the ability of a sports technology to track one or more of the following parameters—heart rate, distance, pace, speed, cadence, style, altitude, and depth — and give users instant access to these data.

Given the above, we propose the following hypotheses to be tested by analyzing perceived innovations in context-aware tracking.

H2. Tracking has a positive impact on the perceived performance expectancy (a), effort expectancy (b), hedonic motivation (c), and habitual use (d) of a sports technology.

Context-aware coaching

Personal trainers, coaches, and physiotherapists help people adjust and correct their exercise practices, reduce the potential for injuries, and minimize health risks. Furthermore, they give feedback and motivate people to improve their overall exercise and training performance.

As defined by this study, advances in sports technologies enable people to "carry their coach" with them anywhere and at any time. Like coaches and trainers, most sports technologies provide feedback to users, push reminders regarding activities, and motivate the pursuit of goals.

Many studies show that sports technologies act as good coaches for various activities, from golf (Ghasemzadeh *et al.*, 2009) to fitness (Novatchkov and Baca, 2013). Hence, we define context-aware coaching as the ability of a sports technology to perform one or more of the following—activity suggestions, stand-up reminders, push notifications on nutrition, and motivational reminders—and provide feedback based on users' goals.

Based on the above, we propose the following hypotheses on context-aware coaching:

H3. Coaching has a positive impact on the perceived performance expectancy (a), hedonic motivation (b), and habitual use (c) of a sports technology.

Context-aware sharing

Sharing, in a sports technology context, involves sharing activity data, events, challenges, and plans with friends. Sharing accomplishments such as earned badges and rewards is typical for this kind of technology. Pizzo *et al.* (2020) reported that wearable fitness technologies could enhance service experience in health and fitness club settings via social interaction. Canhoto and Arp's (2017) qualitative evidence suggests that sharing is an essential factor in the adoption and diffusion of sports technologies. Tu *et al.* (2019) reported that fitness apps focusing on social value demonstrated better performance in walking. Social value focus also increases continued use and motivation. Hence, we define context-aware sharing as features that allow users to share activity data, track friends' activities and data, communicate with others, create chat groups, and organize joint activities with friends.

Given the above, we propose the following hypotheses:

H4. Sharing positively impacts the perceived social influence (a) and habitual use (b) of a sports technology.

Context-aware gamification

Sports technologies possess features such as progress bars, virtual badges and awards, and opportunities to challenge friends. These features are intended to offer more than just perceived enjoyment: they help users achieve their goals and motivate them to stay on track. User interfaces and experience are designed to enhance these features of sports technologies (Pizzo *et al.*, 2020; Ferreira *et al.*, 2021). For instance, Apple's smartwatch series offers a feature comprising three rings that represent movement, exercise, and standing. The user's daily goal is to close all three rings—one of the simplest and stickiest examples of gamification. Apple stated that the three-rings idea is "such a simple and fun way to live a healthier day that you will want to do it all the time" (Apple, 2018a). Polo-Peña et al. (2021) found that gamification has a positive influence on the perceived self-efficacy of sports wearables. They also added that the impact is more significant for women and older people.

There is no single generally accepted definition of gamification. Still, it can be defined as "the use of game mechanics and experience design to digitally engage and motivate people to achieve their goals" (Burke, 2014). Gamification features allow users to earn points and badges from activities and create a competitive environment with friends or other people.

The following hypotheses will be confirmed if perceived innovation characteristics can be explained through context-aware gamification:

H5. Gamification has a positive impact on the perceived performance expectancy (a), effort expectancy (b), social influence (c), habitual use (d), and hedonic motivation (e) of a sports technology.

Conceptual framework

This research aims to understand the effects of sports technology context-awareness characteristics on user acceptance and motivation, sports type, and perceived innovation characteristics. Performance expectancy, effort expectancy, social influence, habit, and hedonic motivation (Venkatesh *et al.*, 2012) are perceived innovation characteristics that mediate between context-awareness elements and behavioral intention to use. Sports motivation (Pelletier *et al.*, 2013) and sports type (Mitchell *et al.*, 2005) are also modeled as grouping variables. The conceptual research model is shown in Figure 1.

[Figure 1 about here]

Venkatesh *et al.* (2018) highlight the importance of adding new exogenous mechanisms to the UTAUT model. For example, Brown *et al.* (2010) utilized technology characteristics as exogenous mechanisms in their study of collaboration technology adoption. Accordingly, we extend the UTAUT2 model with new exogenous mechanisms to explain existing endogenous constructs and deepen understanding of adoption behavior. Our new construct incorporates characteristics of sports technologies into the UTAUT model as antecedents of perceived innovation characteristics. Moreover, whereas few UTAUT studies have tested the effects of group differences (Venkatesh *et al.*, 2018), our study includes sports motivation and type to examine the moderation effects of individual differences.

Methodology

We constructed a survey combining the perceived innovation characteristics scale items from Venkatesh *et al.* (2012), the SMS II items from Pelletier *et al.* (2013), and novel context-awareness scale items to quantitatively measure relationships in the conceptual model.

The definition of sports technology pertinent to this study and pictures of relevant sports technologies were presented to survey participants. Pre-tests and pilot tests were conducted with university students before full-scale implementation of the survey instrument, enabling any misunderstandings or inconsistencies in the wording to be resolved.

To empirically test the model, we recruited 600 participants in Turkey who regularly engage in sports and use sports technologies. The sample comprised 240 females and 360 males, aged 18–50 and with varying income and education levels. The first subgroup (n=244) included people who engage in a dynamic sports activity such as running, walking, or soccer. The second subgroup (n=356) contained people who regularly undertake a non-dynamic sports activity like yoga, Pilates, or weightlifting. Data were collected using a data collection platform similar to Amazon

Mechanical Turk and Prolific. Participants were notified about the survey and the monetary reward for completion before taking the survey. Participation was voluntary. The sample included people practicing various sport types to eliminate the possibility of a single type dominating the sample, which would diminish our results' generalizability. The platform excluded submissions that were incomplete or had missing information.

Partial least squares structural equation modeling (PLS-SEM) was used for model and hypotheses testing via SmartPLS v.3.2.8. (Ringle *et al.*, 2015). PLS-SEM is an emerging method in information systems and marketing, renowned for its robustness in testing theory (Bentler and Huang, 2014; Hair *et al.*, 2017).

Collinearity and common method bias

We assess collinearity with the variance inflation factor (VIF). A VIF value greater than 3.3 is undesirable, while values above 10 indicate a serious collinearity problem (Kock, 2015). The VIF values suggest there is no concern regarding collinearity in our model. Harman's single-factor test assesses common method bias. Variance explained by a single factor needs to be below 50% (Podsakoff *et al.*, 2003). The single factor was responsible for 37.3% of the total variance in the overall model and thus acceptable.

Reliability and validity analysis

We calculated the Cronbach's alpha for each latent construct in the model to assess internal reliabilities. All Cronbach's alphas were above 0.8, indicating construct reliability. The Cronbach's alpha and rho_A values are presented in Table III.

[Table III about here]

To confirm convergent validity, factor loadings should be above 0.5, the average variance extracted (AVE) score of every construct should be above 0.5, and the composite reliability of all constructs should be above 0.7 (Bagozzi and Yi, 2012; Fornell and Larcker, 1981). The detailed scores for each item are reported in Table III. All items in the model demonstrate high convergent validity.

There are two ways to validate discriminant validity: either the square root of AVE values should exceed the R-square values, or the item loadings of a construct should exceed the cross-loadings of the items of other constructs (Fornell and Larcker, 1981). We examined the Heterotrait-Monotrait Ratio (HTMT) for the constructs: all values were below 1.0 and thus acceptable.

Model fit

Model fit measures are unsuitable for (variance-based) PLS-SEM analysis because most are calculated based on the covariance matrix. Nonetheless, some researchers find it useful to mention model fit criteria for PLS-SEM (Hair et al., 2017; Cepeda-Carrión and Cepeda-Carrion, 2018; Toledo and Palos-Sanchez, 2020). SmartPLS software calculates a couple of model fit measures, including SRMR, NFI, d_ULS, d_G, and Chi-square. The upper threshold for SRMR is 0.8, while NFI needs to be higher than 0.9. The other model fit criteria are not commonly used among researchers and need further clarification before use as model fit indicators (Gaskin, 2018; Ringle *et al.*, 2015). The SRMR value of the estimated model is within the desired range, while the NFI value is just below the desired cutoff. Table IV presents the model fit assessment results.

[Table IV about here]

Results

Structural model assessment and hypothesis testing

We tested our causal model with PLS-SEM after finding the reliability and validity results within acceptable ranges. We used PLS bootstrapping with 1,000 subsamples and a 95% confidence interval to test each hypothesis: in any given relationship, the t statistic should be above 1.96 or the *p-value* below .05. We first examined direct relationships. Results for the direct effects are presented in Table V. All direct hypotheses were supported except for the effect of social influence on use intention (H1c). We also analyzed the indirect effect of each context-aware characteristic on use intention through UTAUT2 variables (Table VI). We observed significant results for all total indirect effects. However, several specific indirect effects between context-aware characteristics and use intention were non-significant, including coaching through hedonic value (p = .059), sharing through social influence (p = .246) and habit (p = .086), gamification through social influence (p = .230), and tracking through hedonic value (p = .051).

[Table V about here]

[Table VI about here]

Multi-group analysis

We performed a partial least square multi-group analysis (PLS-MGA) to control for differences in path loading between groups. PLS-MGA compares each group’s statistical scores with the other group's for the same parameter. Comparison of different groups offers valuable insight into a group's behaviors, which is academically and practically advantageous (Hair *et al.*, 2010; Ringle *et al.*, 2015). In PLS-MGA, if the *p-value* for a path estimate difference is higher than 0.95 or lower than 0.05, there is a statistically significant difference between groups (Dijkstra and Henseler, 2015; Dos Santos *et al.*, 2018). We first test measurement invariance using the three-step measurement invariance of the composite model procedure, both for motivation and sports-type groups (Henseler *et al.*, 2016). We obtained full configural invariance (step 1) and compositional invariance (step 2) but partial measurement variance after looking at equality of composite mean values and variances (step 3) (Dos Santos *et al.*, 2020). Table VII provides the compositional invariance assessment results.

[Table VII about here]

Intrinsic vs. extrinsic motivation

The effects of coaching on habit formation and hedonic value on intention to use were statistically significant for intrinsically motivated people but not for the extrinsically motivated. By contrast, the effects of coaching on hedonic motivation and of both social influence and performance expectancy on use intention were significant for extrinsically motivated people but not for the intrinsically motivated. Table VIII reports the path coefficients and *p* values for the two groups.

Dynamic vs. non-dynamic sports

The effect of coaching on habitual use was significant in the non-dynamic sports group but not in the dynamic sports group. Similarly, the effect of gamification on performance expectancy was only significant in the non-dynamic group. By contrast, the effects of hedonic value and performance expectancy on use intention were significant in the dynamic sports group but not in the non-dynamic sports group. Again, Table VIII reports the path coefficients and *p* values for the two groups.

[Table VIII about here]

Discussion

Perceived innovation characteristics and behavioral intention to use

Performance expectancy and relative advantage constructs provide the explanatory power in most acceptance models (Davis, 1989; Venkatesh *et al.*, 2003). Raman and Aashish (2021), Aksoy et al. (2020) and Reyes-Mercado (2018) also found that performance expectancy (similar to perceived usefulness) significantly explains behavioral intention to use fitness wearables. However, Wu *et al.* (2016) reported that relative advantage significantly affects attitudes toward using smartwatches but not behavioral intention to use. Our findings show that performance expectancy is a critical factor for behavioral intention to use sports technologies.

Ease of use (synonymous with effort expectancy) was not a significant predictor of intention to use in Wu *et al.*'s (2016) study, which the authors attribute to ease of use being mainly a firm-level acceptance construct. By contrast, Raman and Aashish (2021), Aksoy et al. (2020), Reyes-Mercado (2018) and Kim and Shin (2016) found that effort expectancy and ease of use had direct positive effects on intention to use. Consistently with the latter set of findings, our results reveal that effort expectancy is the main construct explaining intention to use a sports technology. Like Lunney *et al.* (2016), we find a significant relationship between habit and intention to use. Habit is especially crucial for intrinsically motivated participants in dynamic sports. Canhoto and Arp (2017) indicate that the hedonic features of a sports technology are essential to the user. Our findings support their claim by revealing a direct positive relationship between hedonic motivation and behavioral intention to use.

All the hypotheses are supported except for the effect of social influence on use intention. This relationship was also insignificant in Reyes-Mercado's (2018) quantitative analysis, although that study's qualitative findings revealed that social influence was a significant antecedent of behavioral intention for 26% of the sample. By contrast, Wu *et al.* (2016) found a significant negative relationship between social influence and use intention, although the negative direction of the relationship was not explained. We believe that social influence might be problematic because of cultural differences: its effect on use intention was not empirically supported in Mexico (Reyes-Mercado, 2018) or Turkey (this study). Still, it was in Taiwan (Wu *et al.*, 2016). Additionally, Raman and Aashish reported that social insecurity and discomfort have a negative impact on intention to use sports wearables in India.

Context-awareness characteristics and perceived innovation characteristics

The default feature of sports technologies is tracking. We find tracking to be the strongest indicator of performance (H2a) and effort expectancy (H2b), with respective loadings of 0.313 and 0.502. Tracking also has direct effects on habit and hedonic motivation, together with mediated effects on behavioral intention to use through effort expectancy, habit, and performance expectancy.

In line with Polo-Peña et al. (2021) and Villalobos-Zúñiga and Cherubini's (2020) studies, our findings show that a sports technology's gamification features affect performance expectancy, effort expectancy, social influence, habit, and hedonic motivation. The example of Apple's three-rings feature supports our findings (Apple, 2018a, 2018b): "closing the rings" gives the user a sense of achievement, which in turn improves hedonic motivation. Intention to close the rings every day leads to habitual use, and sharing achievements with friends positively affects social influence.

Intuitively, sharing should be a critical sports technology feature, given that it enables social activity. Robust findings from the qualitative study show that interviewees favored the sharing features of sports technologies. Further analysis in the quantitative study reveals that sharing features significantly impact both social influence (H4a) and habitual use (H4b), with respective loadings of 0.315 and 0.241. These findings are similar to Tu *et al.* (2019), who reported that social features in fitness apps increase users' walking performance.

The sports science literature focuses on using sports technologies to enhance motivation. Our findings reveal that the coaching characteristic of sports technologies indeed promotes habit formation. As Molina and Myrick (2021) reported, modeling behavior and self-challenge are critical for sustained use of fitness apps. Interestingly, we find that coaching also affects social influence. In a social environment, the user's response to instant notifications, such as reminders to stand up or walk, can trigger awareness in the group. The coaching characteristic causes people to check their devices more often, creating interest in the subject in their social circles. Image and visibility constructs (Moore and Benbasat, 1991) have also been used in the literature for similar reasons.

Sports motivation and sports type as grouping variables

Behavioral factors are important when it comes to wearable usage. Raman and Aashish (2021) reported perceptional differences in sports wearables between gym and non-gym members. This study reveals group differences in motivation to use sports technologies. Extrinsically motivated people value the technology characteristic of social influence, whereas intrinsically motivated people do not. Gamification is also found to be an important criterion by which to evaluate performance expectancy for extrinsically motivated people.

Similarly, sports type is found to influence technology adoption. We find that people doing dynamic sports activities, which require more cardiovascular activity, have different reasons to use sports technologies than participants in non-dynamics sports.

Theoretical implications

Our study contributes to the literature on the adoption and continued use of sports technologies that build on existing research (e.g., Barbosa et al., 2021; Cheng et al., 2021; Damberg, 2021). Our four-dimension construct of context-awareness—comprising gamification, tracking, coaching, and sharing—helps to provide better explanations to the drivers behind adoption and continued use. We integrate context-awareness characteristics into the UTAUT2 model as exogenous mechanisms (Venkatesh et al., 2018). The scale items for context-aware characteristics should be further validated in information systems studies for different health and motivational technologies. This new scale can be used with different dependent variables, such as continued or habitual use of different technologies. Incorporating technology characteristics into user-behavior studies will enable researchers to assess acceptance and adoption in a more composite manner.

Previous studies used SDT to examine the interaction between various technology variables and user behavior (Palmeira et al., 2007; Plangger et al., 2019). We used SDT to identify different user groups' behaviour for sports technology usage and its relationship with context-aware characteristics. Our findings revealed that the effect of hedonic value, performance expectancy and social features of technology on usage intention differs for extrinsically and intrinsically motivated people.

Effect of sports type on user behaviour has been studied in different contexts (e.g., smoking and sports type, Gossin et al., 2021). We used medical literature to classify sports activities and examined the impact of sports type—dynamic vs. non-dynamic— on intention to use behavior. Having a sports activity classification would enable future sports marketing studies to analyze the effect of different sport types in different study contexts.

Practical implications

The practical implications of our results are potentially useful for marketers and product developers. Firms can increase user adoption rates by combining targeted personal data with artificial intelligence in their products. Data generated by sports technologies are highly specific. Given the high effect of tracking on performance expectancy, manufacturers should increase their efforts to improve the accuracy of tracked measurements. Gamified elements, coaching features, and the ability to share activity information with friends are critical aspects of intention to use, as per the previous studies (Cheng et al., 2021). Our findings can help sports technology brands develop better product user engagement by adopting various context-aware features.

When designing sports technologies, product managers should also consider different user groups based on sports participation and motivation. We identified differences between people who do dynamic and non-dynamic sports and people who are intrinsically and extrinsically motivated to do sports. For example, a dynamic sports activity application for the low autonomous motivation target group should concentrate particularly on coaching features. In contrast, sharing and gaming features are more effective in a non-dynamic sport application designed for the low motivation target group. In their communication campaigns, marketers can utilize the most pertinent context-awareness characteristics for specific market segments, such as the different groups we identified.

Limitations

This research has several limitations. First, participants were purposively selected among people who regularly engage in sports activities. Second, our study covers both hardware (e.g., wearable devices) and software (e.g., apps) as sports technologies. Given that almost all devices need an app to communicate with the user, possible limitation effects exist. Third, although the original UTAUT2 model includes price as the perceived cost of the technology, our model omits this dimension because both free and paid tools are considered in this study. Finally, previous studies reported differences in sports activity choice based on cultural norms and religious beliefs (Agergaard, 2016). We did not incorporate cultural differences in sports participation and involvement.

Future research

The context-awareness characteristics analyzed in this study can also apply to other high-tech products available on the market, such as Amazon Echo or similar technologies. Future studies incorporating context-awareness characteristics could examine possible differences in acceptance behavior with respect to free and paid-for sports technologies. It would also be valuable to test and validate the scale items of context-aware characteristics in other areas that require healthy habit behavior, such as smoking cessation or diet. Finally, as this study did not investigate how cultural differences affect the adoption of sports technologies, this unexplored facet may serve as the primary construct in future research.

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Table I

Survey items for context-awareness characteristics

Characteristic	Items
Tracking	My X tracks and displays my performance. My X collects the activity data that I need (pulse, distance, depth, speed, pace, cadence, etc.). Data measurement by my X is sufficiently instantaneous to meet my needs. My X presents the collected data in a format that I can easily understand.
Sharing	My X has the capability to allow me to follow friends' activities. My X allows me to share information about my activities with friends. My X has social features (sharing, following, etc.) that use information about my activity. My X possesses features (group chat, activity planning, etc.) that enable me to communicate with friends.
Coaching	My X provides useful tips and advice regarding my activities. My X coaches me while carrying out my activities. My X motivates me to perform my activities. My X helps me reach my goals.
Gamification	My X has gamification features (virtual badges, scoreboard, prizes, etc.) My X allows me to reach my goals in a fun way. My X has features that enable me to compete with friends. My X has features that make me feel like I am playing a game.

Note. X refers to a sports technology as defined in the Introduction.

Table II

Correlations and reliability measures for context-awareness characteristics

	Tracking	Coaching	Sharing	Gamification	AFL	α	Items
Tracking	1				0.795	0.847	4
Coaching	0.486	1			0.798	0.866	4
Sharing	0.525	0.491	1		0.715	0.867	4
Gamification	0.431	0.591	0.567	1	0.727	0.877	4

Note: AFL, average factor loading, α, Cronbach's alpha. (N=257)

Table III

Construct reliability and validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted
Coaching	0.827	0.829	0.828	0.547
Effort	0.845	0.846	0.843	0.574
Gamification	0.813	0.817	0.814	0.523
Habit	0.899	0.907	0.900	0.695
Hedonic	0.904	0.905	0.904	0.702
Intention	0.893	0.893	0.893	0.675
Performance	0.856	0.856	0.855	0.542
Sharing	0.869	0.869	0.869	0.624
Social	0.915	0.918	0.915	0.729
Tracking	0.801	0.801	0.800	0.600

Note: N = 600

Table IV

Model fit assessments

	Saturated model	Estimated model
SRMR	0.045	0.068
d_ULS	1.708	3.938
d_G	0.801	0.936
Chi-square	2,377.141	2,721.992
NFI	0.852	0.830

Table V

Direct effects and significance of the hypothesized paths

	Path	Path coefficient
H1	(a) Performance expectancy → Intention to use	0.150*
	(b) Effort expectancy → Intention to use	0.184**
	(c) Social influence → Intention to use	n.s
	(d) Hedonic motivation → Intention to use	0.153*
	(e) Habitual use → Intention to use	0.259**
H2	(a)Tracking → Performance expectancy	0.313**
	(b)Tracking → Effort expectancy	0.502**
	(c)Tracking → Hedonic motivation	0.336**
	(d) Tracking → Habitual use	0.216**
H3	(a) Coaching → Performance expectancy	0.290**
	(b) Coaching → Hedonic motivation	0.192**
	(c) Coaching → Habitual use	0.175**
H4	(a) Sharing → Social influence	0.241**
	(b) Sharing → Habitual use	0.315**
H5	(a) Gamification → Performance expectancy	0.223**
	(b) Gamification → Effort expectancy	0.205**
	(c) Gamification → Social influence	0.292**
	(d) Gamification → Habitual use	0.339**
	(e) Gamification → Hedonic motivation	0.259**

Table VI

Specific and total indirect effects

Indirect path	**Path coefficient**	***p***
Coaching → Habit → Intention	0.035	0.022
Coaching → Hedonic → Intention	0.022	0.059
Coaching → Performance → Intention	0.039	0.018
Coaching total indirect effect → Intention	0.096	0.000
Gamification → Effort →Intention	0.038	0.001
Gamification → Habit →Intention	0.062	0.001
Gamification → Hedonic → Intention	0.034	0.039
Gamification → Performance → Intention	0.037	0.012
Gamification → Social →Intention	0.017	0.230
Gamification total indirect effect→ Intention	0.189	0.000
Sharing →Habit →Intention	0.023	0.086
Sharing →Social →Intention	0.015	0.246
Sharing total indirect effect → Intention	0.039	0.035
Tracking →Effort →Intention	0.096	0.001
Tracking →Habit →Intention	0.047	0.005
Tracking →Hedonic →Intention	0.042	0.051
Tracking →Performance →Intention	0.057	0.007
Tracking total indirect effect → Intention	0.242	0.000

Table VII

Compositional invariance assessment

Variable	Intrinsic vs. Extrinsic		Dynamic vs. Non-dynamic		Compositional invariance?
	c	5% quantile of c_u	c	5% quantile of c_u	
Coaching	0.998	0.997	1.000	0.995	Yes
Effort	1.000	0.999	1.000	0.999	Yes
Gamification	1.000	0.998	1.000	0.998	Yes
Habit	1.000	0.999	1.000	0.999	Yes
Hedonic	0.999	0.998	1.000	1.000	Yes
Intention	1.000	0.999	1.000	0.999	Yes
Performance	0.998	0.997	0.999	0.999	Yes
Sharing	1.000	0.997	0.999	0.998	Yes
Social	1.000	0.999	0.999	0.999	Yes
Tracking	0.998	0.997	1.000	0.998	Yes

Notes: Compositional invariance requirement: c > 5% quantile of cu.

Table VIII

Multi-group model assessments

Path	Motivation		Sports Type	
	Intrinsic	**Extrinsic**	**Dynamic**	**Non-dynamic**
Coaching → Habit	0.191*	0.095	0.129	0.201**
Coaching → Hedonic	0.119	0.201**	No significant difference	
Gamification → Performance	No significant difference		0.163	0.281**
Hedonic → Intention	0.055*	0.150	0.202*	0.145
Performance → Intention	0.108	0.177*	0.175*	0.144
Social → Intention	-0.004	0.168*	No significant difference	

Note. * $p < .05$; ** $p < .01$

Figure 1

Research Model