GIST do it! How motivational mechanisms help wearable technology users develop healthy habits

Abstract

Wearable devices and other smart technologies are becoming widely popular as more individuals adopt the goal of improving their health. Users of such devices are exploiting technology in their struggle to combat poor sedentary habits that have been shown to have severe consequences for physical and mental wellness. Using the U-Commerce perspective, this study goes beyond user adoption studies to examine how motivational technology characteristics help users sustain their motivation and acquire habitual behaviors. Specifically, we propose a model that shows how autonomous motivation leads to habitual intentions predicated upon user preferences for different motivational features, namely gaming, instructing, sharing, and tracking (or, as we have termed them, GIST). After developing user preference measures, we empirically test the GIST model in a large sample with diverse characteristics to identify motivational differences by gender and age. We find that autonomous motivation has a significant, fully mediated impact on habitual intentions through the app mechanisms of gamification, instruction, and tracking. Although the mechanism of sharing is still important for habitual purposes, this effect does not significantly change with differences in autonomous motivation. We close with future directions for motivational technology research and health management practice.

Keywords: Wearable devices; Motivational technology; Habit formation; Gamification; Tracking; U-Commerce

1. Introduction[1]

Across genders and age groups, individuals are focusing on health improvement goals such as losing weight, exercising more, stopping smoking, or increasing physical activity (Sundel & Sundel, 2017). However, despite such efforts to adopt healthy lifestyles, obesity is listed as a cause of at least 2.8 million deaths globally each year (World Health Organization, 2017). The main reason for this statistic is an insufficient physical activity, primarily due to sedentary lifestyles (World Health Organization, 2018). One of the greatest ironies of human nature is that most individuals understand why they need to be physically active and how to do it, yet many do not (Segar, 2015). Motivational technologies, which combine wearable technologies (e.g., smartwatches, smart wristbands) with mobile app-based nudging strategies, provide hope as tools to develop and sustain healthy habits. The enhanced technological capabilities (e.g. evolved Internet of Things (IoT), AI-enabled computing) (Ameen et al., 2021; Ferreira et al., 2021) and social value of such technologies have contributed to their increased adoption (Tu et al., 2019; Niknejad et al., 2020).

Although motivational technologies are being widely trialed, there are challenges in encouraging their long-term use and adoption to develop and sustain users' healthy habits. Often, individuals start a new fitness regime with big goals; however, when they fail to achieve these goals quickly, their motivation decreases, and they stop using motivational technologies despite the initial investment (Parker-Pope, 2020). Sales of motivational technologies have slumped in past years (Lamkin, 2018); however, the COVID-19 pandemic has inverted this trend as individuals have more time to focus on self-care and are—now more than ever—using the

[1] Abbreviations

GIST: gaming, instructing, sharing, and tracking

RAI: relative autonomous index

various features that these technologies offer, including tracking progress, suggesting or rewarding pro-health behaviors, and sharing results with (distant) friends (Milanesi, 2020). The impact of these supportive device features on continued use are discussed in various articles from different perspectives, such as social value (Tu et al., 2019) and gamification attributes (Feng et al., 2020; Soni et al., 2021; Bitrián et al., 2020). Guided by self-determination theory (Ryan & Deci, 2000) and the U-Commerce framework (Watson et al., 2002), this paper assesses four features of motivational technologies that offer the most assistance to individuals in improving their health through sustained and increased use of such technologies. We use the term motivational technologies to cover a broader scope, referring to all technologies that help users enhance and sustain their physical and mental health; these include smartwatches, smart wrist bands, diet apps, smoking cessation apps and apps, fitness apps, and other types of m-health apps and gadgets.

Although genetic, social, cultural, and historical factors are the main determinants of the mismatch between health goals and actual behavior (Harvard Health Letter, 2008), these goals can be achieved using motivational techniques that have effects on internal and external self-determined processes (Pelletier et al., 2013; Ryan & Deci, 2000). Although increasing activity levels and maintaining a healthy weight is rewarding, the rewards are often seen as distant or long-term for many individuals, and as such, are difficult to achieve without continuous motivation. Self-control (i.e., the self's control over the self; Muraven & Baumeister, 2000) and self-regulation (i.e., the self's capacity to adjust its actions; Baumeister & Vohs, 2007) are critical for increasing and maintaining motivation to achieve health goals; however, many individuals require a motivation intervention to boost their chances at achieving these goals (Segar, 2015).

Recent technological advancements allow wearable devices, in combination with mobile apps, to track and monitor fitness activities and provide motivational feedback to their users (Hirvonen et al., 2015; Huang & Ren, 2020; Novatchkov & Baca, 2013). These technologies are a reflection of U-Commerce, which conceptualizes "use of ubiquitous networks to support personalized and uninterrupted communications and transactions between a firm and its various stakeholders to provide a level of value over, above, and beyond traditional commerce" (Watson et al. 2002, p. 336). Similarly, motivational wellbeing technologies utilize ubiquitous communication and exchange of information between users and applications, regardless of time, hardware, location, or context. Motivational fitness technologies are ubiquitous and enable users to monitor important body metrics by employing artificial intelligence and machine-learning algorithms to provide unique specific tailored feedback based on users' data (Huang & Ren, 2020; Lee et al., 2016). Moreover, these fitness apps allow universal goal progress sharing (Canhoto & Arp, 2017; Tu et al., 2019) and context-aware gamification elements (Dix et al., 2004; Robson et al., 2015) to further assist users in achieving health goals.

The business literature provides some insight into the effectiveness of motivational technologies in changing behavior (Lee & Cho, 2017; Lyons & Swartz, 2017; Feng et al., 2020; West et al., 2017) as well as these technologies' adoption and diffusion (Canhoto & Arp, 2017; Huang & Ren, 2020; Kim & Chiu, 2019; Lunney et al., 2016; Wu et al., 2016). However, many past studies focus primarily on technological solutions for a single problem, e.g., for smoking cessation (Haskins et al., 2017; Morriscey et al., 2019) or diet modification (Halse et al., 2019). Although product-related variables (e.g., product superiority, relative advantage, newness, degree of customization) have been used in innovation diffusion studies to an extent (Goodhue, 1995; Harmancioglu et al., 2009; Huang & Ren, 2020), further studies are needed for conceptualizing the continued usage of new motivational technologies. Owing to the capabilities afforded by artificial intelligence and hypersensitive sensors, motivational technologies are constantly improving in terms of their context-aware product features; however, only a small number of studies investigate and assess the differential effectiveness of the motivational components of these technologies—gaming, instructing, sharing, and tracking—based on users' characteristics (see Table 1 for a summary of relevant papers).

Table 1

Selected studies on technology-mediated motivational strategies

Study	Technology and Context	Motivational Features				Users' Differences	
		Gaming	Instructing	Sharing	Tracking	Gender	Age
Boendermaker et al. (2015)	Reduce heavy drinking	X		X			
Bricker et al. (2014)	Reduce/stop smoking		X		X		
Hamari and Koivisto (2015)	Increase exercise habits	X		X			
Koivisto and Hamari (2014)	Increase exercise habits	X		X	X	X	X
Lee and Cho (2017)	Continue to use diet/fitness apps			X	X	X	
Nelson et al. (2016)	Health empowerment	X	X		X		
Plangger et al. (2019)	Increasing physical activity	X			X		
Huang and Ren (2020)	Continue to use fitness mobile apps		X		X		
This study	Healthy habit formation	X	X	X	X	X	X

This paper makes several contributions: first, by applying self-determination theory (Ryan & Deci, 2000) and the U-Commerce framework (Watson et al. 2002), we construct a conceptual typology of four types of features of motivational technologies: gaming, instructing, sharing, and tracking. Second, we develop and test a research model with six hypotheses showing the differential effectiveness in creating and sustaining fitness habits based on users' gender and age. Third, we show that different gender and age groups perceive distinct motivational features differently. Females and older people have higher preferences in these motivational features across all motivation levels.

Before constructing the research model, this paper explores the information systems, consumer behavior, behavioral economics, and marketing literature for insights and conceptualizations of motivational features. Then, we test the research model using 240 female and 360 male participants and find that context-aware motivational elements fully mediate the relationship between autonomous motivation and habit formation. We close with a discussion of the results and their research and practical implications, as well as offer suggestions for future research.

2. Conceptual Development

2.1. Habit Formation through Autonomous Regulation

Although their technological adoption is essential to understand (Chuah et al., 2016; Lunney et al., 2016; Wu et al., 2016), the success of motivational technologies depends on the effectiveness with which they enable individuals to achieve health goals by establishing habitual use of these technologies (Limayem et al., 2007; Royer et al., 2015; Villalobos-Zúñiga & Cherubini, 2020). Liu and Avello (2021) shared in their bibliometric analysis that motivation is used as a keyword by only 1.7% in fitness app-related research. There are many motivational technologies on the market that aim to help people improve their diets, exercise habits, or other pro-health behaviors; however, without habitual usage, their effectiveness is short-term. Habit is defined as "the extent to which people tend to perform behaviors automatically because of learning" (Limayem et al., 2007). According to self-determination theory (Ryan & Deci, 2000), habits can be developed either through intrinsic (i.e., within the individual) or extrinsic (i.e., outside the individual) motivational means. The theory proposes that competence, autonomy, and relatedness are three inherent psychological needs that, when fulfilled, generate improved self-motivation and mental health, and when not fulfilled, lead to weakened motivation and well-being. When initial levels of motivation are low, extrinsic interventions are critical to not only encourage users to try motivational technologies, but also to sustain their use to achieve goals (Plangger et al., 2019; Molina & Myrick, 2020). For example, in smoking cessation studies, users that receive benefits from smoking cessation apps are more successful in reducing or ceasing their smoking behaviors (Haskins et al., 2017; Morriscey et al., 2019). Thus, technological features that bolster extrinsic motivation are vital in not only convincing users to attempt fitness regimes, but also in nurturing the intrinsic motivation required for continued commitment to achieving fitness goals (Plangger et al., 2019).

Nurturing intrinsic motivation leads to an increase in individuals' *autonomous regulation* of behaviors (Pelletier et al. 1995). Autonomous regulation is associated with increased task versus ego involvement (Ryan & Deci, 2000), intrinsic objectives (Sheldon et al., 2004), approach versus avoidance orientations (Keatley et al., 2012), magnified subjective well-being (Deci & Ryan, 2008), and enhanced physical activity (Duncan et al., 2017). Motivation plays a vital role in habit formation by stimulating behavioral repetition. Physical activity fueled by intrinsic motivation tends to be sustained and can become habit (Gardner & Lally, 2013). Repetition has a strong effect on habit where behavior is triggered by extrinsic motivation such as reward mechanisms. Motivational technologies can enhance repetitive behavior by providing external control and in turn, help to create motivational changes. Changes in repetitive behavior can modify habits because a habit can also be defined as "a cognitive-motivational process, conceptually distinct from behavior" (Gardner, 2015).

By adapting two influential scales (Sports Motivation Scale, Pelletier et al., 1995; Sports Motivation Scale 2, Pelletier et al., 2013), Rottensteiner et al. (2015) validated the *relative autonomous index (RAI)*, which is a single numerical measure indicating the relative influence of intrinsic and extrinsic sources of motivation to achieve a goal. This index quantifies whether the scope of individuals' motivation for their behaviors to engage in a particular activity is autonomously regulated or externally controlled. RAI has been applied to physical activity settings, and the results have shown a direct effect of relative autonomy on habit that is stronger than the influence of past behavior (Gardner & Lally, 2013). Apart from its application to the physical activity context, RAI has been found to have a significant and positive impact on behavioral automaticity (a proxy for habit) for 12 different behaviors, including but not limited to running, going to the gym, smoking, drinking alcohol, and eating chips (Radel et al., 2017). In other words, as the level of autonomous motivation increases, the habits become stronger. Formally,

H1: Autonomous motivation (RAI) has a positive impact on habitual usage of a motivational technology.

2.2. Context-Aware Technologies and Motivational Features

Aided by wearable sensor technologies, context awareness includes understanding of where (i.e., location-awareness), when (i.e., time-awareness), what (i.e., activity-awareness), and why (i.e., goal-awareness) users are doing what they are doing (Dix et al., 2004). Context-aware technologies utilize data on users' physical, social, informational, and emotional situation as input to adjust the performance of their analytical outcomes (Abowd et al., 1998). Context-aware capabilities that promote behavior change are enabled by gaming features intended to increase user engagement (Plangger et al., 2019), instructing features tailored to individual goals (Pyky et al., 2017), sharing features to publicly report goal-specific data (Nelson et al., 2016), and tracking features to individually assess and benchmark performance (Attig & Franke, 2019).

Motivational technologies' context-aware features can be rationalized and mapped using the U-Commerce framework's (Watson et al., 2002) dimensions: ubiquity, universality, uniqueness, and unison (see Table 2). *Ubiquity* is found in motivational technologies because they are everywhere, and at the same time "nowhere": because they are so embedded in our lives, we do not notice their presence. *Universality* refers to the availability and accessibility of technology and its data. *Uniqueness* is near fully realized with motivational technologies, given that users receive customized information based on their time, location, and expressed or learned preferences. *Unison* refers to transparent data transmission across devices, which is a common feature in many motivational technologies. Thus, motivational technologies employ accessible (i.e., universal) networks to support personalized (i.e., unique), consistent (i.e., unison), and continuous (i.e., ubiquitous) interactions between users and their wearable devices to provide enhanced motivation to achieve goals. We explore these further in the next four sections.

Table 2

U-Commerce applied to motivational technologies

Dimensions	Definition	Motivational Features			
		Gaming	Instructing	Sharing	Tracking
Ubiquity	Unconditional access to information	X	X	X	X
Uniqueness	Context-aware information	X	X	X	X
Unison	Information consistency			X	
Universality	Transferable information	X		X	

Gaming features are applications of gamification, or principles of game design applied to elicit emotional and behavioral responses in users (Robson et al., 2015; Burke, 2014). Not all consumption activities are undertaken as a result of logical, rational decisions: some originate in fantasies, feelings, and fun (Holbrook & Hirschman, 1982), leading many studies to use hedonic motivation (i.e., perceived enjoyment) as a predictor of usage intention (Venkatesh et al., 2012). Motivational technologies often incorporate gaming features, such as point collection, virtual achievement badges, status levels, virtual awards, and leaderboards to illustrate users' progress relative to their friends. Gaming features increase perceived enjoyment (Koivisto & Hamari, 2014) and are critical for users to not only visualize their goals, but also to constantly motivate themselves to stay on track to achieve these goals. Using wearable device performance data (uniqueness) seamlessly and continuously (ubiquity) in concert with apps (universality), gaming features enable engaging environments that often have dynamic storylines or game-like experiences, leading to goal achievement (Plangger et al., 2019). Because users are engaged in the game-like experience, gaming features act as distractions from an otherwise uninteresting or difficult-to-achieve goal, compelling users to habitually use motivational technology.

Furthermore, at the same time, this habitual use rewards activities that are essential for achieving goals. Formally,

H2: Autonomous motivation (RAI) leads to increased usefulness perceptions of gamification features that further increase habitual use of motivational technologies.

According to studies on the trans-theoretical model (Prochaska et al., 2009; Prochaska & Marcus, 1994), *instructing features* that provide tailored feedback are effective at changing physical activity habits (Hirvonen et al., 2012; Pyky et al., 2017). These features mirror personal trainers, dietitians, life coaches, and physiotherapists in their function to aid users in adjusting and correcting their exercise routines, improving their diet, preventing injuries, and acquiring healthy habits (Nelson et al., 2016). Using wearable device data that are constantly being updated (ubiquity), instructing features include simple "push" reminders nudging users to start or continue activities (uniqueness) or more complex instructions that coach users in reaching their goals (uniqueness). Instructing features have been applied in motivational technologies to improve sport performance (Ghasemzadeh et al., 2009; Novatchkov & Baca, 2013), stop smoking (McClure et al., 2017), and losing weight (Hirvonen et al., 2015; Jakicic et al., 2016; Pyky et al., 2017). To increase physical activity levels, instructing features often include activity suggestions, stand up reminders, move notifications, nutritional alerts, motivational notifications, and other feedback. Instructing features of motivational technologies encourage habitual use that may lead to goal fulfilment (Bricker et al., 2014; Nelson et al., 2016). Thus, we hypothesize:

H3: Autonomous motivation (RAI) leads to increased usefulness perceptions for instructing features that further increase habitual use of motivational technologies.

Sharing features disclose users' data on their achievements with other users or even external individuals (e.g., coaches, doctors). A key reason behind sharing behavior is gaining social currency that is useful for establishing positive impressions among similar individuals (Berger, 2016). These features are often key to adoption and diffusion (Canhoto & Arp, 2017), and users share their data with their social community which makes them more likely to progress towards and eventually achieve their goal (Bradford et al., 2017), often by developing healthy habits (Uetake & Yang, 2019). Moreover, wearable devices enable the sharing of not only a continuous, real-time, activity data stream (ubiquity), but also of an event, a challenge, or a plan with social connections (universality). Sharing features also provide for the conspicuous sharing of accomplishments (e.g., badges, rewards, leaderboard positions) (uniqueness) that are common features of a particular app and are intended to increase the motivation levels of other users (unison) (Piskorski & Johnson, 2012). Hence, sharing features permit users to share their activity data with others, keep track of social connections' activities and accomplishments, communicate with others, create chat groups, and set up joint activities with friends.

H4: Autonomous motivation (RAI) leads to increased usefulness perceptions for sharing features that further increase the habitual use of motivational technologies.

Tracking features allow motivational technologies to collect data on the user who is wearing the device, including for example, their location, body movements, heart rate, pace, speed, dive depth, sleep quality, or swim strokes. While this collection might activate privacy concerns (e.g., Okazaki et al., 2020; Plangger & Montecchi, 2020), users can visually access their exercise history anytime and anywhere (ubiquity) using graphs, charts, or other visual representations that are produced behind the scenes by intelligent systems (Pyky et al., 2017). Moreover, users also receive notifications and reminders based on their activity history and other contextual factors (uniqueness) that can promote additional unplanned exercise (Hirvonen et al., 2015). Thus, these features provide useful benefits that encourage continued adoption and habitual use (Nelson et al., 2016). Tracking features enable intrinsically motivated users to assess their performance for self-improvement purposes, encouraging the habit use of wearable technology (Lee & Cho, 2017). Thus,

H5: Autonomous motivation (RAI) leads to increased usefulness perceptions of tracking features that further increase the habitual use of motivational technologies.

2.3. Users' Preferences for Motivational Features

As motivation research finds (Brunet & Sabiston, 2011; Teixeira et al., 2012), users' characteristics often have a differential impact on the efficacy of motivational interventions, or, in this paper, on that of motivational features. Specifically, a user's age and gender have been shown to either magnify or diminish the effectiveness of certain motivational features; however, little is understood about how these features work in concert to promote habitual usage of wearable fitness technologies. Evaluation of smart wearables, such as watches, wristbands, or glasses, as a combination of technology and fashion (a.k.a. fashnology) (Rauschnabel, 2016) can be helpful to understand age and gender differences relevant to continued use of those technologies. Although Chuah et al. (2016) did not report any gender or age effects on wearable adoption based on the fashnology perspective, previous studies have reported that males are more technology-oriented (Chang et al., 2014) and women are more fashion-oriented (Handa & Khare, 2013).

Considering *age* differences first, many recent studies (e.g., Hirvonen et al., 2015; Lee & Cho, 2017; Pyky et al., 2017) call for further investigation into the impact of age on habitual use of motivational technologies, given that reported evidence is mixed and often only reported as a footnote to the main study. On the one hand, technology adoption research reports that younger users are more comfortable with using these technologies, which require a learning process, to achieve goals (e.g., Venkatesh et al., 2003). Younger adults seem to have better outcomes in variety of settings, including, for example, weight loss (Jakicic et al., 2016), sports participation (Ha et al., 2015), and smoking cessation (McClure et al., 2017). However, on the other hand, older users often—post-adoption—insist on motivational features that increase their enjoyment (Wu et al., 2016) and interaction with technology (Koivisto & Hamari, 2014). Therefore, although younger users may adopt these technologies more easily, they may not fully utilize motivational features to gain these positive outcomes compared with older users (see the Method section for more details on age classifications). Formally:

H6: Younger users (versus older users) experience a diminished impact of autonomous motivation (RAI) on habitual usage through (a) gaming, (b) instructing, (c) sharing, and (d) tracking features.

Moving on to *gender differences,* the literature reports mixed findings when investigating different preferences for physical activities between men and women. Some physical activity studies report significant gender differences: for example, compared with men, women are twice as likely to search for physical activity information (Berry et al., 2011), have higher commitment to their exercise regimes (Royer et al., 2015) and report higher intentions to continue exercising (Hamari & Koivisto, 2015). However, men are more likely to be early adopters of fitness wearable technologies (Canhoto & Arp, 2017; Venkatesh et al., 2003). Moreover, men are more likely to prefer utilitarian features of wearable technologies, whereas women are found to prefer hedonic ones (Venkatesh et al., 2012). Gupta et al. (2020) reported that Generation Y Indian males preferred smartwatches, while females preferred fitness trackers. In contrast, a couple of studies report that gender has no significant impact on smartwatch adoption (Chuah et al., 2016; Wu et al., 2016) or attitudes toward diet or fitness apps (Cho et al., 2015). While male users may adopt motivational technologies more easily, female users may utilize motivational features to build positive, sustainable habits. Thus, we hypothesize:

H7: Female users (versus male users) experience a magnified impact of autonomous motivation (RAI) on habitual usage through (a) gaming, (b) instructing, (c) sharing, and (d) tracking features.

2.4. The GIST Model

In short, users' autonomous motivations inspire habitual use of wearable fitness devices, both directly and indirectly, through four motivational features of these technologies: gaming, instructing, sharing, and tracking. Furthermore, users' preferences for these features depend on the users' characteristics, namely, their age and gender. Figure 1 illustrates our conceptual framework, termed the GIST model to increase its memorability.

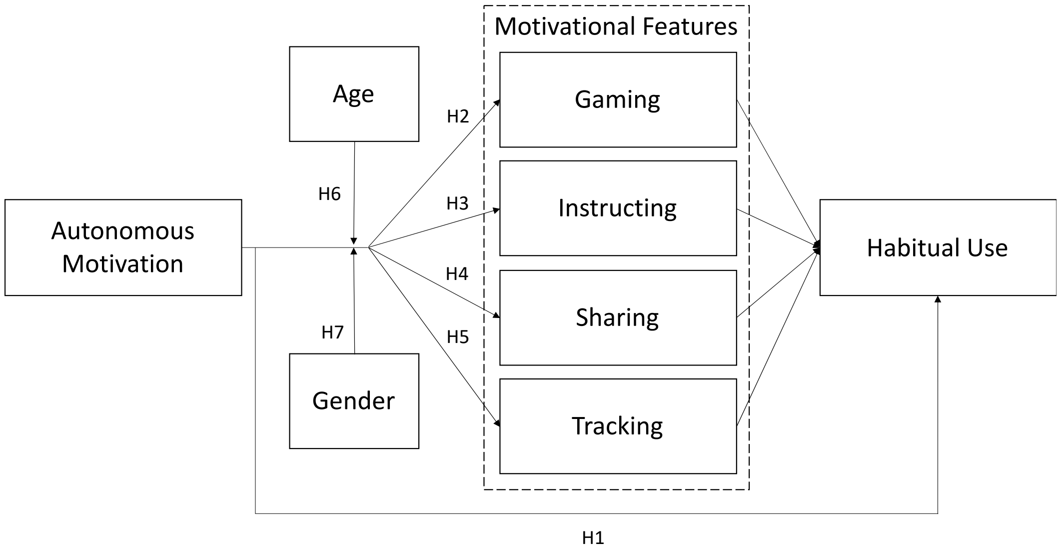

Fig. 1. The GIST Model

3. Measuring Motivational Feature Preferences

In order to investigate how context-aware features of motivational technologies facilitate the relationship between users' motivation and their behavioral change, we sought to conduct a quantitative survey using validated measurement scales for dependent and independent constructs and developed a scale to measure motivational feature preferences. Our dependent construct, habitual usage, was measured using scale items from Venkatesh et al. (2012). Our independent construct, autonomous motivation, was measured using Pelletier et al. (2013)' Relative Autonomous Index (RAI). Although some studies explore the utility of motivational features (see Table 1), there is no validated scale to measure users' preference for the context-aware features of motivational technologies, thus necessitating the development of a new scale.

Following Mackenzie et al. (2011)'s scale development procedure, we constructed a measurement scale to assess users' preferences for motivational features. After defining the study domain and conducting an extensive literature review, we created 17 items that were assessed by independent judges to ensure content adequacy (Churchill, 1979; Mackenzie et al., 2011).

Specifically, to assess the four context-aware characteristics, we asked seven academic experts in marketing and information systems to assign each item to the most suitable motivational feature. Only one scale item that had a high disagreement rate was dropped from the scale. For all other items, at least six of the seven judges agreed that our predicted classifications were applicable, with an average agreement of 90%. As a result, 16 survey items remained with which to measure the context-aware motivational features.

Table 3
Exploratory factor analysis

Motivational Feature	Scale Items*	Factor Loadings
Sharing	I think that my X has enough social features (sharing, following, etc.) that use my activity information.	0.874
	My X allows me to share information about my activities with my friends.	0.836
	I think my X allows me to follow my friends' activities.	0.824
	There are features (group chat, activity planning, etc.) that allow me to communicate with my friends in my X.	0.748
Instructing	My X coaches me to do my activities.	0.888
	I am motivated by my X to be active.	0.815
	My X helps me reach my goals.	0.710
	My X provides useful tips and advice for my activities.	0.679
Tracking	My X measures the activity data that I need.	0.886
	My X tracks my performance in my activities to show me my progress.	0.814
	The data measured by my X are current enough to meet my needs in my activities.	0.679
	My X presents my data in a format that I can easily understand.	0.533
Gaming	I think there are some features in my X that make me feel like I am playing a game.	0.782
	My X allows me to reach my goals in a fun way.	0.725
	My X has gaming features (virtual badges, scoreboard, prizes, etc.) related to my activities.	0.642
	I think my X enables me to compete with my friends.	0.549

* Please note that “X” denotes the respondent’s brand of motivational device.

While independent judges provided face validity, we tested the scale’s construct validity and reliability and further purified it using a sample of 257 respondents from a major European business school (Churchill, 1979). Using Smart PLS, confirmatory factor analysis was conducted to evaluate motivational feature convergent validity (see Table 3) and motivational feature discriminant validity (see Table 4). Higher factor loadings indicate better convergent validity (Liaukonyte et al., 2014); in this study, average factor loadings were high, signifying acceptable convergent validity. All of the cross-correlations were lower than .07, which means there is no significant shared variance between the factors (Hair et al., 2010), indicating acceptable discriminant validity. Reliability indicators such as Cronbach's alpha assess the consistency of the errors and variance in a single factor; therefore, we calculated this statistic for each motivational feature and found that all were above 0.7, which confirms the reliability scale (Hair et al., 2010).

Table 4
Correlations

Motivational	Correlation				Reliability		
Feature	Gaming	Instructing	Sharing	Tracking	AFL*	α	Item n
Gaming	1				0.795	0.847	4
Instructing	0.649	1			0.798	0.866	4
Sharing	0.613	0.482	1		0.715	0.867	4
Tracking	0.456	0.576	0.567	1	0.727	0.877	4

Note: As the factor loadings for Gaming 3, Instructing 2, and Tracking 4 scale items were less than 0.7, an analysis without these three factors was conducted and no significant differences in the results were found; therefore, we kept these items.
*AFL = Average Factor Loading

4. Method

To test our conceptual model, we developed a quantitative survey that combined our new scale to assess users' preferences for motivational features with existing measures to evaluate users' habitual usage (Venkatesh et al., 2012) and relative autonomous index (RAI) scale items (Pelletier et al., 2013). Pre-tests and pilot tests were conducted with a student sample from a large Turkish university before full-scale implementation to check for any misunderstandings or inconsistencies.

4.1. Sample and Procedure

Using an online panel and a mobile platform popular in Turkey, the study was carried out with a heterogenous, purposive sample of 360 men and 240 women between 18 to 50 years old of various income and education levels who are regularly physically active and use motivational technologies. Because of the limited user behavioral research in emerging economies in the information systems literature (Goncalves et al., 2018; Srivastava & Shainesh, 2015), Turkey was chosen as our empirical site because of the country's high adoption rate of wearable fitness devices (Euromonitor, 2020) and the prevalence of fitness goals among individuals (Statista, 2020). The sample including individuals practicing various types of fitness or sports activities to eliminate the possibility of having a single dominant activity type in the sample that could limit the generalizability of the findings.

After voluntarily accepting the survey and providing their informed consent, participants were presented with relevant definitions and pictorial examples of motivational technologies and their features. Then, they answered a randomized series of questions concerning the motivational feature preferences, RAI, and habitual usage. Last, participants recorded their answers to a set of simple demographic questions before being awarded a small monetary reward.

Analysis Plan

Following best practice (Sun & Zhong, 2020; Weinstein & Przybylski, 2019), we used PROCESS macro on SPSS to measure our moderated mediation model. PROCESS employs ordinary least squares for parameter estimations, a general approach for path analysis of observed variables (Hayes, 2017). We chose to use PROCESS because bootstrapping was found to be one of the most effective methods to measure mediation; moreover, conducting a moderated mediation analysis in a complex model is uncomplicated with this macro (Preacher & Hayes, 2008). Moreover, there is no significant difference between the usage of structural equation modeling and PROCESS macro tools when analyzing a model with entirely observed variables (Hayes et al., 2017). We tested a mediation model (Model 4) and a moderated mediation model using Hayes (2017) PROCESS macro (Model 8 and 10). We employed 5000 bootstrap samples and 95% bias-corrected confidence intervals for the bootstrapping procedure because of the sample size. We report both beta coefficients (denoted by *b*) and effect sizes (denoted by *d*) depending on the nature of the statistic, that is whether direct or indirect, in the following section.

5. Results

Table 5 reports the results of the base mediation model (Model A) and the moderated mediation models (Models B, C, and D). In Model A, although RAI (relative autonomous index or autonomous motivation in this study) does not have a significant direct effect on habitual use intentions in all tested models (b=.0024, p=.460), thus not supporting H1, RAI affects habitual use intention mediated by three of the four features of motivational technologies. Specifically, in Model A, higher RAI significantly increases habitual use intentions through preferences for gamification (d=.0027, LLCI=.0007, ULCI=.0053), instructing (b=.0039, LLCI=.0015, ULCI=.0069), and tracking features (d=.0048, LLCI=.0022, ULCI=.0077), supporting H2, H3, and H5. While preferences for sharing features have positive impacts on habitual use intentions, preferences for sharing features are not significantly affected by RAI in Model A (d=-.003, LLCI=-.0014, ULCI=.0009), not supporting H4. Our results showed that even though there is no direct effect of motivation on habit formation, the relationship is mediated by motivational technology characteristics. We obtained differing results for different motivational features. For example, instructing, tracking, and gamification are significant mediators between RAI and habitual use in all models (partial support in Model D for tracking and gamification), showing that consumers' demand for these features are critical for their continued use. Sharing, in contrast, is not a significant mediator between RAI and habitual use: the effect is moderated by age and gender. We also found that the tracking feature is more important for older users. Further analysis on age and gender moderations was conducted with Model B, C, and D below.

Model B tested the conditional effects of users' age on the impact of RAI on the motivational features in the base mediation model ($\Delta R^2_{\text{(Model B–Model A)}}$=.0042). Higher user age significantly increased the effect of RAI on gamification (b=.0015, p<.001), instructing (b=.0007, p=.043), sharing (b=.0013, p=.004), and tracking (b=.0007, p=.009), such that older (versus younger) users have increased preferences for the features of motivational technologies, supporting H6abcd. In Model B, age did not have a conditional effect on the direct impact of RAI on habitual use intention (b=.0002, p=0.540).

Model C tested the conditional effects of users' gender on the impact of RAI on the motivational features in the base mediation model ($\Delta R^2_{\text{(Model C–Model A)}}$=.0115). Female users reported significantly increased effects of RAI on gamification (b=.0143, p=.036), instructing (b=.0135, p=.014), sharing (b=.0234, p=.001), and tracking (b=.0087, p=.041), such that women (versus men) users have increased preferences for the features of motivational technologies, supporting H7abcd. Gender has a conditional effect on the direct impact of RAI on habitual use intention (b=.0176, p=.005), such that women with high autonomous motivation significantly report higher levels of habitual use of motivational technologies. Our results revealed that there is a significant direct effect of motivation on habitual use for female users.

After testing the conditional effects of age (Model B) and gender (Model C) independently in Models B and C, Model D tests both moderating variables' impact on autonomous motivation (RAI) on habitual use intentions through the users' preferences for features of motivational technologies ($\Delta R^2_{\text{(Model D–Model A)}}$ =.0144). Although the results are largely similar between conditional effects models, Model D offers a more nuanced analysis showing the differential contribution of each variable to explaining variance. For instance, the interactions with "instructing" are significant in both Models B and C, but only the interaction of "instructing" and "gender" is significant in Model D (b=.0128, p=.022), suggesting that gender is a more important user characteristic than age for the "instructing" feature (b=.0005, p=.128). By applying the "pick-a-point" method (Montoya, 2018; Sun & Zhong, 2020) to Model D's results, Figures 2 and 3 illustrate users' preferences for features of motivational technologies and their autonomous motivation (RAI) for age and gender, respectively. In the figures, we used age categories automatically calculated by PROCESS Macro for our continuous scale age variable: average age 35.3 years (young), average age 44.2 years (middle), average age 53.2 years (old).

6. Discussion

Responding to calls for empirical investigations into the habitual use of motivational technologies (Attig & Franke, 2020; Lunney et al., 2016), this study offers contributions by examining the mediating role of various features of motivational technologies that enable users to act on their autonomous motivations and form habits. Moreover, this study explores how users' characteristics—namely, their age and gender—influence the effect of users' autonomous motivation on their preferences for gaming, instructing, sharing, or tracking features of motivational technologies. Explaining 38.6% of the variance in habitual use intention (Model D), the results provide important implications not only for academics but also for technology design and fitness industry managers. Based on these findings, behavior change programs and motivational technologies can be tailored to elicit healthy habits among users depending on their own characteristics and feature preferences. Table 6 provides a summary of the results obtained by testing the hypotheses. The next two sections discuss the implications of our findings for academic research and managerial practice.

Table 5

Results

Model (Process Macro Number)	Model A (4)	Model B (8)	Model C (8)	Model D (10)	
	b (SE)	*b* (SE)	*b* (SE)	*b* (SE)	
Direct Effects					
RAI → Habit	.0036 (.0033)	–.0046 (.0124)	–.0042 (.0040)	–.0065 (.0124)	
RAI → Gaming	.0096** (.0033)	–.0347** (.0133)	.0032 (.0042)	–.0355** (.0134)	
RAI → Instructing	.0142*** (.0027)	–.0073 (.0109)	.0087* (.0034)	–.0072 (.0109)	
RAI → Sharing	–.0029 (.0035)	–.0418** (.0140)	–.0121** (.0044)	–.0438** (.0140)	
RAI → Tracking	.0165*** (.0021)	–.0049 (.0084)	.0130*** (.0026)	–.0049 (.0084)	
Gaming → Habit	.3054*** (.0550)	.3016*** (.0551)	.3118*** (.0546)	.3094*** (.0548)	
Instructing → Habit	.2780*** (.0653)	.2824*** (.0653)	.2602*** (.0652)	.2643*** (.0652)	
Sharing → Habit	.1137* (.0474)	.1140* (.0473)	.0997* (.0472)	.1010* (.0472)	
Tracking → Habit	.2881*** (.0734)	.2804*** (.0741)	.2817*** (.0735)	.2765*** (.0736)	
	d (SE)	*d* (SE)	*d* (SE)	*d* (SE)	*d* (SE)
Indirect Effects (*Moderation*)	(*No Moderation*)	(*Age*)	(*Gender*)	(*Gender*)	(*Age*)
RAI → Gaming → Habit	.0027* (.0011)	.0004* (.0002)	.0045* (.0022)	.0037 (.0021)	.0004* (.0001)
RAI → Instructing → Habit	.0039* (.0014)	.0002* (.0001)	.0035* (.0019)	.0034* (.0019)	.0001* (.0001)
RAI → Sharing → Habit	–.0003 (.0005)	.0001* (.0001)	.0023 (.0016)	.0022 (.0016)	.0001* (.0001)
RAI → Tracking → Habit	.0047* (.0014)	.0002* (.0001)	.0024* (.0014)	.0021 (.0014)	.0004* (.0001)
Interaction Effects					
RAI × Age → Habit		.0002 (.0004)		.0001 (.0004)	
RAI × Age → Gaming		.0015*** (.0004)		.0013** (.0004)	
RAI × Age → Instructing		.0007* (.0004)		.0005 (.0004)	
RAI × Age → Sharing		.0013** (.0005)		.0011* (.0005)	
RAI × Age → Tracking		.0007** (.0003)		.0006* (.0003)	
RAI × Gender → Habit			.0176** (.0063)	.0167** (.0063)	
RAI × Gender → Gaming			.0143* (.0068)	.0120 (.0068)	
RAI × Gender → Instructing			.0135* (.0055)	.0128* (.0055)	
RAI × Gender → Sharing			.0234** (.0071)	.0217** (.0071)	
RAI × Gender → Tracking			.0087* (.0043)	.0075 (.0043)	
R^2	.3716	.3758	.3831	.3860	

Note: Unstandardized b coefficients (with boot SE between parentheses); BCBCI = bias-corrected 5,000 bootstrap confidence interval;
*** p < .001; ** p < .01; * p < .05.

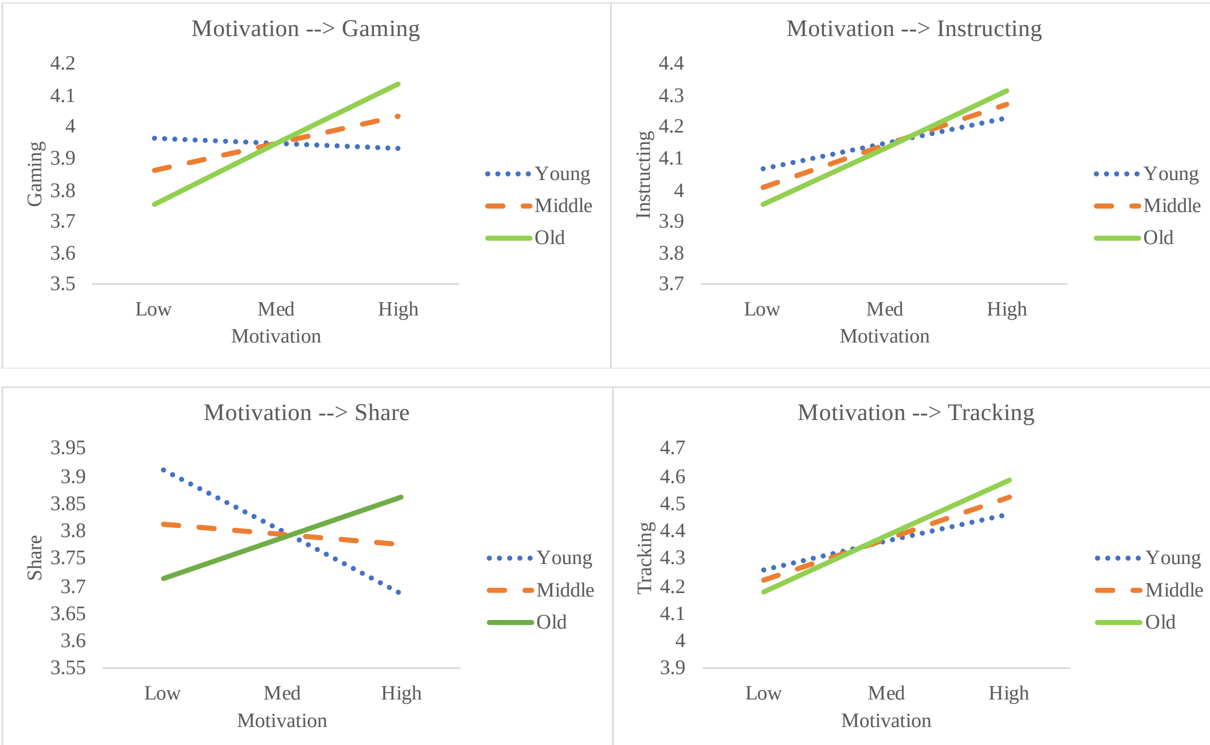

Fig. 2. Effects of user age on preferences for features of motivational technologies.

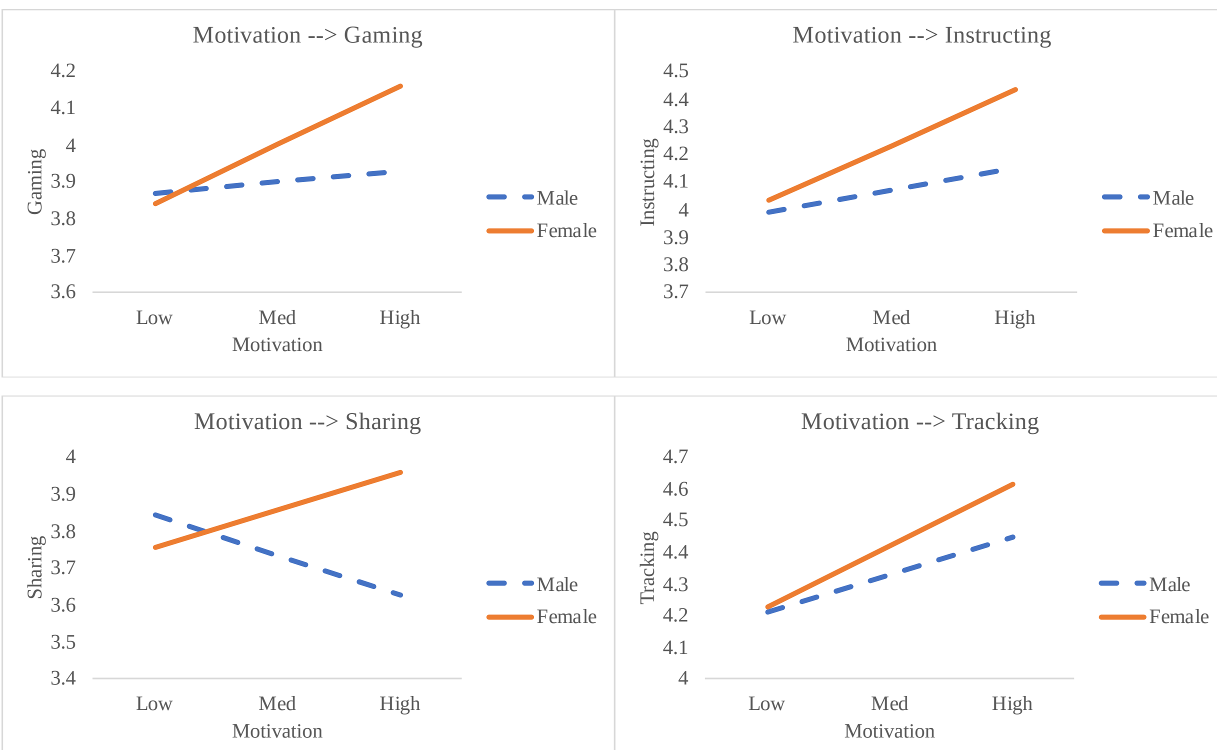

Fig. 3. Effects of gender on preferences for features of motivational technologies

6.1. Theoretical implications

This study examines the impact of four context-aware features—gaming, instructing, sharing, and tracking—of motivational technologies on habitual use intentions that build on existing research examining users' perceptions of device performance and usability (e.g., Chuah et al., 2016; Lunney et al., 2016; Wu et al., 2016). Enhanced sensor technologies increased wearable devices' capability, and in turn, the users' overall experiences were positively affected. Consumers are sensitive to device features when it comes to purchasing decisions, and their long-term use is also affected by technological capabilities. We identified the importance of GIST for habit formation in the context of motivational technologies.

The importance—and difficulty of—habit formation in smoking cessation, losing weight and sports activities have been covered in previous studies (Bradford et al., 2017; Hamari & Koivisto, 2015; Haskins et al., 2017; Royer et al., 2015) Studies have attempted to link motivation and sustainable healthy behavior (Gardner & Lally, 2013; Segar, 2017). Gardner and Lally (2013) unexpectedly found a direct effect of relative autonomy on habit strength, but also reported limitations on the causal direction of observed effects: thus, direction and strength of the link need more support. Unlike previous research that applies Self Determination Theory to understand its interaction with various motivation technology variables and user behavior (Palmeira et al., 2007; Plangger et al., 2019), we utilized Self Determination Theory to explore how the relationship between motivation and habit is mediated by GIST variables. Our findings revealed that even though there is no direct effect of motivation on habit formation, the relationship is mediated by motivational technology characteristics. Additionally, we found that there is a significant direct effect of motivation on habitual use for female users.

Table 6

Summary of Findings

Hypotheses		Findings from Model A	B	C	D
H1	*Autonomous motivation* (RAI) has a positive impact on the *habitual usage* of a motivational technology.	X	X	X	X
H2	*Autonomous motivation* (RAI) leads to increased usefulness perceptions for *gaming features* that further increase the habitual use of motivational technologies.	✓	✓	✓	P
H3	*Autonomous motivation* (RAI) leads to increased usefulness perceptions for *instructing features* that further increase the habitual use of motivational technologies.	✓	✓	✓	✓
H4	*Autonomous motivation* (RAI) leads to increased usefulness perceptions for *sharing features* that further increase the habitual use of motivational technologies.	X	✓	X	P
H5	*Autonomous motivation* (RAI) leads to increased usefulness perceptions for *tracking features* that further increase the habitual use of motivational technologies.	✓	✓	✓	P
H6	*Younger users* (versus older users) experience a diminished impact of autonomous motivation (RAI) on habitual usage through (a) *gaming*, (b) *instructing*, (c) *sharing*, and (d) *tracking* features.		a:✓ b:✓ c:✓ d:✓		a:✓ b:X c:✓ d:✓
H7	*Female users* (versus male users) experience a magnified impact of autonomous motivation (RAI) on habitual usage through (a) *gaming*, (b) *instructing*, (c) *sharing*, and (d) *tracking* features.			a:✓ b:✓ c:✓ d:✓	a:X b:✓ c:✓ d:X

Note: Results indicate ✓ (support), X (no support), or P (partial support) for hypotheses. Blank entries denote untested relationships in certain models

Tracking is a prerequisite of other GIST variables. There have been questions on the accuracy of tracked data (Gjoreski et al., 2016); at the same time, the need for evidence-based features has been stated (Haskins et al., 2017). Tracking in our GIST model takes into account the accuracy dimension of the data and finds that there is no perceived problem with tracking. Tracking is a significant mediator between RAI and habitual use in all models (partial support in Model D), showing that consumers' demand for these features are critical for their continued use. We also found that the tracking feature is more important for older users. Gender is found to be an important moderator in Model C, with female users being found to favor tracking more compared with male users. However, when age is introduced as a moderator with gender in Model D, the influence of gender is not statistically significant.

Our findings are in line with those of previous studies on the effect of game-like elements in motivational devices on habit formation (Hamari & Koivisto, 2015; Robson et al., 2015). Gaming is a potent mediator between motivation and habitual usage in all models (partial support found in Model D). The effect is more substantial for older and female consumers.

Nelson et al. (2016) examined gaming, instructing, and tracking among the four GIST variables, but specified the need for incorporation of the social aspects of a motivational technology to better understand its effects on pro-health behavioral change. Building on this call, we incorporated sharing as the social dimension in our GIST framework to measure its impact on sustainable healthy behavior formation. Even though sharing is not a significant mediator between RAI and habitual use, the effect is moderated by age and gender. The sharing feature is more important for older and female users. Our finding is consistent with previous research reporting that women value the social aspects of exercise technologies more than men do (Koivisto & Hamari, 2014). Receiving feedback and healthy tips from motivational technologies, as offered by the "instructing" feature in our model, is of utmost importance for supporting healthy habit formation (Hirvonen et al., 2015; Hoeppner et al., 2016; Nelson et al., 2016). Our findings confirm that "instructing" is a significant mediator in all models. The effect is also moderated by age and gender, wherein older and female users value instructing features more.

6.2. Managerial implications

By understanding the relationships between autonomous motivation and the processes of habit formation, technology or app designers can better produce engaging experiences using motivational features to encourage users' healthy habits. For example, designers aiming to create an app for an older female target user group with low autonomous motivation should concentrate particularly on instructing features, while also including other motivational features. In contrast, younger user target groups with low motivation show more engagement with sharing and gaming features that lead them to establish healthy habits. Habit formation is not necessarily confined to health-related behaviors, but also to other areas where sustainable actions are needed such as financial savings, ecologically friendly consumption decisions, socially responsible choices, employee job performance, or other wellbeing behaviors.

7. Conclusions

7.1. Limitations and Future Research Avenues

As with all empirical studies, this research has a few limitations. First, the study focuses on those who regularly participate in sport and fitness activities and their use of wearable motivational technologies. However, future study of individuals that are not as active would be potentially useful to explore in order to build on and extend the GIST framework and deepen the conceptualization of motivational technology and behavior change facilitation. Furthermore, while fitness is at the heart of this research, the GIST framework could potentially be applied to other healthy habit behavior change domains such as smoking cessation, weight loss, or disease management, as well as non-health contexts.

Second, in attempting to test which motivational features are associated with habitual use, our study only looks at individuals who own a wearable device. These individuals might have unique attributes or characteristics (e.g., increased levels of technology savviness, market mavenism, and need for uniqueness) that may be associated with greater autonomous motivation or an increased likelihood of healthy habit formation. Therefore, future studies could incorporate wider samples of individuals—those that both own and do not own wearable devices—to test whether there are any differences due to wearable ownership status.

Last, although we identify four critical motivational features that encourage habitual use of wearable technologies, there might be untested technological features, other factors, or novel innovations that are important. For example, blood oxygen detection is starting to become a common feature of wearable fitness devices, and different ways of using this information might further enhance the motivational drive to establish fitness habits. An extension of the GIST model with different technological features could unearth additional insights.

Table 7 summarizes possible future research directions and offers managerial guidelines.

Table 7: Future Directions for Research and Practice

Strategic area	Potential questions for future research	Managerial guidance
New product development	• How can instructing features be better tailored to individual user characteristics? • To what extend different configurations of gamification features increase habitual usage? • Which GIST feature is more attractive to people undertaking dynamic sports activities? • Can we identify different segments based on GIST feature usage?	Different features have a different level of importance for various user segments. Managers should take into account distinct GIST features when creating new motivational technology.
Marketing and advertising	• Which GIST features would serve better to improve communication campaign effectiveness for different demographics? • Who are the most effective influencers to help to promote motivational technologies? How can they be used in a communication campaign? • Which media are the best for promoting motivational technology? • To what extent can GIST framework be applied financial sector? Can GIST features help to create sustainable saving behavior? Or, to control spending behavior?	Our research found that females value the sharing feature more than males do. Managers could benefit from this type of difference among the target audience when creating their communication campaigns.
Consumer wellbeing and satisfaction	• Beyond age and gender, what other user characteristic, behavioral, or attitudinal differences can explain habitual usage of motivational technologies? • What is the role of access to fitness facilities and the impact of GIST features on habitual usage and wellbeing? • How much do GIST features improve user engagement for motivational technologies? • Which GIST features are serving best for improving user engagement? • To what extent does using GIST features improve customer satisfaction? •	Engagement is one of the crucial metrics for application performance. Managers can make use of different GIST features to improve user engagement. This study finds autonomous motivation level is an essential factor that affects consumer perceptions towards GIST features. Managers can identify other segments by using GIST framework.
Employee wellbeing and satisfaction	• How can technological products inside the company promote healthy habit formation? • To what extent can the GIST framework be used to reduce employee absenteeism? • Is there a relationship between employee healthy habit formation and corporate performance?	Managers can use the GIST framework to enhance healthy habit formation in the company and create team spirit among employees; in turn, employee job performance may be improved.

7.2. Concluding thoughts

Although specific goals may differ (e.g., losing weight, gaining muscle mass, becoming fitter), many individuals seek to develop healthy habits through the use of wearable technologies with motivational features (e.g., Nelson et al., 2016). However, after an initial (short) period of sustained use, users often stop using these technologies because sustainable habits have yet to be formed (e.g., Hamari & Koivisto, 2015). This article offers a conceptual understanding of how the motivational features of wearable technologies (i.e., gaming, instructing, sharing, and tracking) can facilitate the development of heathy habits in intrinsically motivated users. Our empirical study tests the GIST model and shows that, for different kinds of users, the effectiveness of the motivational features differs. These findings offer practical insight into how managers should more finely target users when developing and supporting new products and solutions. Furthermore, in addition to being useful in conceptualizing the role of motivational features in habit formation, the GIST model may also provide a useful framework for exploring motivation and habit formation in other settings.

REFERENCES

Abowd, G. D., Dey, A., Orr, R., & Brotherton, J. (1998). Context awareness in wearable and ubiquitous computing. *Journal of Virtual Reality*, *3*(3), 200–211.

Ameen, N., Hosany, S., & Tarhini, A. (2021). Consumer interaction with cutting-edge technologies: Implications for future research. *Computers in Human Behavior*, *120*, 106761.

Attig, C., & Franke, T. (2019). I track, therefore I walk – Exploring the motivational costs of wearing activity trackers in actual users. *International Journal of Human Computer Studies*, *127*(April 2018), 211–224. https://doi.org/10.1016/j.ijhcs.2018.04.007

Baca, A., Kornfeind, P., Preuschl, E., Bichler, S., Tampier, M., & Novatchkov, H. (2010). A server-based mobile coaching system. *Sensors*, *10*(12), 10640–10662. https://doi.org/10.3390/s101210640

Baumeister, R. F., & Vohs, K. D. (2007). Self-regulation, ego depletion, and motivation. *Social and Personality Psychology Compass*, *1*(1), 115–128. https://doi.org/10.1111/j.1751-9004.2007.00001.x

Berger, J. (2016). *Contagious: Why things catch on*. Simon and Schuster.

Berry, T. R., Spence, J. C., Plotnikoff, R. C., & Bauman, A. (2011). Health communication physical activity information seeking and advertising recall. *Health Communication*, *26*(3), 246–254. https://doi.org/10.1080/10410236.2010.549810

Bitrián, P., Buil, I., & Catalán, S. (2020). Gamification in sport apps: The determinants of users' motivation. *European Journal of Management and Business Economics*, *29*(3), 365–381.

Boendermaker, W. J., Boffo, M., & Wiers, R. W. (2015). Exploring elements of fun to motivate youth to do cognitive bias modification. *Games for Health Journal*, *4*(6), 434–443. https://doi.org/10.1089/g4h.2015.0053

Bradford, T. W., Grier, S. A., & Henderson, G. R. (2017). Weight loss through virtual support communities: A role for identity-based motivation in public commitment. *Journal of Interactive Marketing*, *40*, 9–23. https://doi.org/10.1016/j.intmar.2017.06.002

Bricker, J. B., Mull, K. E., Kientz, J. A., Vilardaga, R., Mercer, L. D., Akioka, K. J., & Heffner, J. L. (2014). Randomized, controlled pilot trial of a smartphone app for smoking cessation using acceptance and commitment therapy. *Drug and Alcohol Dependence*, *143*(1), 87–94. https://doi.org/10.1016/j.drugalcdep.2014.07.006

Brunet, J., & Sabiston, C. M. (2011). Exploring motivation for physical activity across the adult lifespan. *Psychology of Sport and Exercise*, *12*(2), 99–105. https://doi.org/10.1016/j.psychsport.2010.09.006

Burke, B. (2014). *Gamify. How gamification motivates people to do extraordinary things* (1st ed.). Bibliomotion, Incorporated. https://doi.org/10.4324/9781315230344

Canhoto, A. I., & Arp, S. (2017). Exploring the factors that support adoption and sustained use of health and fitness wearables. *Journal of Marketing Management*, *33*(1–2), 32–60. https://doi.org/10.1080/0267257X.2016.1234505

Chang, C. S., Liu, E. Z. F., Sung, H. Y., Lin, C. H., Chen, N. S., & Cheng, S. S. (2014). Effects of online college student’s Internet self-efficacy on learning motivation and performance. *Innovations in Education and Teaching International*, *51*(4), 366–377.

Cho, J., Lee, H. E., Kim, S. J., & Park, D. (2015). Effects of body image on college students' attitudes toward diet/fitness apps on smartphones. *Cyberpsychology, Behavior, and Social Networking*, *18*(1), 41–45. https://doi.org/10.1089/cyber.2014.0383

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016).

Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, *65*, 276–284. https://doi.org/10.1016/j.chb.2016.07.047
Churchill, G. A. (1979). A paradigm for developing better measures of marketing constructs. In *Journal of Marketing Research*, *16*(1), 64–73.
Dix, A., Finley, J., Abowd, G. D., & Beale, R. (2004). *Human–computer interaction* (3rd ed.). Prentice-Hall.
Duncan, M., Eyre, E., Bryant, E., Seghers, J., Galbraith, N., & Nevill, A. (2017). Autonomous motivation mediates the relation between goals for physical activity and physical activity behavior in adolescents. *Journal of Health Psychology*, *22*(5), 595–604. https://doi.org/10.1177/1359105315609089
Euromonitor (2020). *Wearable electronics in Turkey*. Retrieved from https://www.portal.euromonitor.com/portal/analysis/tab. Accessed January 25, 2021.
Feng, W., Tu, R., & Hsieh, P. (2020). Can gamification increases consumers' engagement in fitness apps? The moderating role of commensurability of the game elements. *Journal of Retailing and Consumer Services*, *57*, 102229.
Ferreira, J. J., Fernandes, C. I., Rammal, H. G., & Veiga, P. M. (2021). Wearable technology and consumer interaction: A systematic review and research agenda. *Computers in Human Behavior*, *118*, 106710.
Gardner, B. (2015). A review and analysis of the use of "habit" in understanding, predicting and influencing health-related behaviour. *Health Psychology Review*, *9*(3), 277–295. https://doi.org/10.1080/17437199.2013.876238
Gardner, B., & Lally, P. (2013). Does intrinsic motivation strengthen physical activity habit? Modeling relationships between self-determination, past behaviour, and habit strength. *Journal of Behavioral Medicine*, *36*, 488–497. https://doi.org/10.1007/s10865-012-9442-0
Ghasemzadeh, H., Loseu, V., & Jafari, R. (2009). Wearable coach for sport training: A quantitative model to evaluate wrist-rotation in golf. *Journal of Ambient Intelligence and Smart Environments*, *1*(2), 173–184. https://doi.org/10.3233/AIS-2009-0021
Gjoreski, M., Gjoreski, H., Luštrek, M., & Gams, M. (2016). How accurately can your wrist device recognize daily activities and detect falls? *Sensors*, *16*(6), 800. https://doi.org/10.3390/s16060800
Goncalves, G., Oliveira, T., & Cruz-Jesus, F. (2018). Understanding individual-level digital divide: Evidence of an African country. *Computers in Human Behavior*, *87*, 276–291. https://doi.org/10.1016/j.chb.2018.05.039
Goodhue, D. L. (1995). Understanding user evaluations of information systems. *Management Science*, *41*(12), 1827–1844. https://doi.org/10.1287/mnsc.41.12.1827
Gupta, M., Sinha, N., Singh, P., & Chuah, S. H. W. (2020). Gender differences in the wearable preferences, device and advertising value perceptions: Smartwatches vs. fitness trackers. *International Journal of Technology Marketing*, *14*(2), 199–225.
Ha, J. P., Kang, S. J., & Ha, J. (2015). A conceptual framework for the adoption of smartphones in a sports context. *International Journal of Sports Marketing and Sponsorship*, *16*(3), 2–19. https://doi.org/10.1108/IJSMS-16-03-2015-B002
Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson Education.
Halse, R. E., Shoneye, C. L., Pollard, C. M., Jancey, J., Scott, J. A., Pratt, I. S., ... & Kerr, D. A. (2019). Improving nutrition and activity behaviors using digital technology and tailored feedback: Protocol for the tailored diet and activity (ToDAy) randomized controlled trial.

JMIR Research Protocols, *8*(2), e12782.
Hamari, J., & Koivisto, J. (2015). "Working out for likes": An empirical study on social influence in exercise gamification. *Computers in Human Behavior*, *50*, 333–347. https://doi.org/10.1016/j.chb.2015.04.018
Handa, M., & Khare, A. (2013). Gender as a moderator of the relationship between materialism and fashion clothing involvement among Indian youth. *International Journal of Consumer Studies*, *37*(1), 112–120.
Harmancioglu, N., Droge, C., & Calantone, R. J. (2009). Theoretical lenses and domain definitions in innovation research. *European Journal of Marketing*, *43*(2), 229–263. https://doi.org/10.1108/03090560910923319
Harvard Health Letter (2008). Why we should exercise – and why we don't. Retrieved from https://www.health.harvard.edu/newsletter_article/why-we-should-exercise-and-why-we-dont. Accessed August 28, 2018.
Haskins, B. L., Lesperance, D., Gibbons, P., & Boudreaux, E. D. (2017). A systematic review of smartphone applications for smoking cessation. *Systematic Reviews*, *7*, 292–299. https://doi.org/10.1007/s13142-017-0492-2
Hayes, A. (2017). *Introduction to mediation, moderation, and conditional process analysis*. Guilford Publications.
Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal*, *25*(1), 76–81. https://doi.org/10.1016/j.ausmj.2017.02.001
Hirvonen, N., Enwald, H., Bath, P. A., Pyky, R., Korpelainen, R., & Huotari, M.-L. (2015). Individual factors affecting preferences for feedback message tactics in the contexts of physical activity. *Journal of Health Communication*, *20*(2), 220–229. https://doi.org/10.1080/10810730.2014.925015
Hirvonen, N., Huotari, M.-L., Niemelä, R., & Korpelainen, R. (2012). Information behavior in stages of exercise behavior change. *Journal of the American Society for Information Science and Technology*, *63*(9), 1804–1819. https://doi.org/10.1002/asi.22704
Hoeppner, B. B., Hoeppner, S. S., Seaboyer, L., Schick, M. R., Wu, G. W. Y., Bergman, B. G., & Kelly, J. F. (2016). How smart are smartphone apps for smoking cessation? A content analysis. *Nicotine and Tobacco Research*, *18*(5), 1025–1031. https://doi.org/10.1093/ntr/ntv117
Holbrook, M. B., & Hirschman, E. C. (1982). The experiential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research*, *9(2)*, 132–140.
Huang, G., & Ren, Y. (2020). Linking technological functions of fitness mobile apps with continuance usage among Chinese users: Moderating role of exercise self-efficacy. *Computers in Human Behavior*, *103*, 151–160.
Jakicic, J. M., Davis, K. K., Rogers, R. J., King, W. C., Marcus, M. D., Helsel, D., … Belle, S. H. (2016). Effect of wearable technology combined with a lifestyle intervention on long-term weight loss: The IDEA randomized clinical trial. *JAMA – Journal of the American Medical Association*, *316*(11), 1161–1171. https://doi.org/10.1001/jama.2016.12858
Keatley, D., Clarke, D. D., & Hagger, M. S. (2012). Investigating the predictive validity of implicit and explicit measures of motivation on condom use, physical activity and healthy eating. *Psychology & Health*, *27*(5), 550–569.
Kim, K. J., & Shin, D.-H. (2016). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research*, *25*(4), 527–541.

Kim, T., & Chiu, W. (2019). Consumer acceptance of sports wearable technology: The role of technology readiness. *International Journal of Sports Marketing and Sponsorship*, *20*(1), 109–126. https://doi.org/10.1108/IJSMS-06-2017-0050

Koivisto, J., & Hamari, J. (2014). Demographic differences in perceived benefits from gamification. *Computers in Human Behavior*, *35*, 179–188. https://doi.org/10.1016/j.chb.2014.03.007

Lamkin, P. (2018). Smartwatch popularity booms with fitness trackers on the slide. *Forbes*. Retrieved from https://www.forbes.com/sites/paullamkin/2018/02/22/smartwatch-popularity-booms-with-fitness-trackers-on-the-slide/#7fa8cad7d96d. Accessed January 25, 2021.

Lee, H. E., & Cho, J. (2017). What motivates users to continue using diet and fitness apps? Application of the uses and gratifications approach. *Health Communication*, *32*(12), 1445–1453. https://doi.org/10.1080/10410236.2016.1167998

Lee, J., Kim, D., Ryoo, H. Y., & Shin, B. S. (2016). Sustainable wearables: Wearable technology for enhancing the quality of human life. *Sustainability*, *8*(5), 466. https://doi.org/10.3390/su8050466

Liaukonyte, J., Teixeira, T., & Wilbur, K. C. (2015). Television advertising and online shopping. *Marketing Science, 34*(3), 311–330.

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705–737.

Liu, Y., & Avello, M. (2021). Status of the research in fitness apps: A bibliometric analysis. *Telematics and Informatics*, *57*, 101506.

Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. *Computers in Human Behavior*, *65*, 114–120. https://doi.org/10.1016/j.chb.2016.08.007

Lyons, E. J., & Swartz, M. C. (2017). Motivational dynamics of wearable activity monitors. *ACSM's Health and Fitness Journal*, *21*(5), 21–26. https://doi.org/10.1249/FIT.0000000000000324

Mackenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, *35*(2), 293–334.

McClure, E. A., Baker, N. L., Carpenter, M. J., Treiber, F. A., & Gray, K. M. (2017). Attitudes and interest in technology-based treatment and the remote monitoring of smoking among adolescents and emerging adults. *Journal of Smoking Cessation*, *12*(2), 88–98. https://doi.org/10.1017/jsc.2015.15

Milanesi, C. (2020, June 10). The growing value of wearables. *Forbes*. Retrieved from https://www.forbes.com/sites/carolinamilanesi/2020/06/10/the-growing-value-of-wearables/#46eabaf523bc

Molina, M. D., & Myrick, J. G. (2020). The ‘how’and ‘why’of fitness app use: Investigating user motivations to gain insights into the nexus of technology and fitness. *Sport in Society*, *24*(7), 1–16.

Montoya, A. K. (2018). Moderation analysis in two-instance repeated measures designs: Probing methods and multiple moderator models. *Behavior Research Methods, 51,* 61–82. https://doi.org/10.3758/s13428-018-1088-6

Morriscey, C., Shephard, A., Van Houdt, A., Kerr, D., & Barrett, S. P. (2019). Using "smart" technology to aid in cigarette smoking cessation: Examining an innovative way to monitor

and improve quit attempt outcomes. *Journal of Smoking Cessation*, *14*, 149–154. https://doi.org/10.1017/jsc.2018.33
Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin*, *126*(2), 247–259. https://doi.org/10.1037/0033-2909.126.2.247
Nelson, E. C., Verhagen, T., & Noordzij, M. L. (2016). Health empowerment through activity trackers: An empirical smart wristband study. *Computers in Human Behavior*, *62*, 364–374. https://doi.org/10.1016/j.chb.2016.03.065
Niknejad, N., Ismail, W. B., Mardani, A., Liao, H., & Ghani, I. (2020). A comprehensive overview of smart wearables: The state of the art literature, recent advances, and future challenges. *Engineering Applications of Artificial Intelligence*, *90*, 103529.
Novatchkov, H., & Baca, A. (2013). Artificial intelligence in sports on the example of weight training. *Journal of Sports Science and Medicine*, *12*, 27–37.
Okazaki, S., Eisend, M., Plangger, K., de Ruyter, K., & Grewal, D. (2020). Understanding the strategic consequences of customer privacy concerns: A meta-analytic review. *Journal of Retailing*, *96*(4), 458–473. https://doi.org/10.1016/j.jretai.2020.05.007
Palmeira, L. A., Teixeira, J. P., Branco, L. T., Martins, S. S., Minderico, S. C., & Barata, T. J. (2007). Predicting short-term weight loss using four leading health behavior change theories. *International Journal of Behavioral Nutrition and Physical Activity*, *4*(14), 61–71. https://doi.org/10.1186/1479-Received
Parker-Pope, T. (2020, February 18). How to build healthy habits. *The New York Times*. Retrieved from https://www.nytimes.com/2020/02/18/well/mind/how-to-build-healthy-habits.html
Pelletier, L. G., Fortier, M., Vallerand, R. J., Brière, N. M., Tuson, K., & Blais, M. R. (1995). The sport motivation scale (SMS). *Journal of Sport & Exercise Psychology*, *17*(19), 35–53. https://doi.org/10.1037/a0012801
Pelletier, L. G., Rocchi, M. A., Vallerand, R. J., Deci, E. L., & Ryan, R. M. (2013). Validation of the revised sport motivation scale (SMS-II). *Psychology of Sport and Exercise*, *14*(3), 329–341. https://doi.org/10.1016/j.psychsport.2012.12.002
Piskorski, M. J., & Johnson, R. (2012). Social strategy at Nike. Harvard Business Review, April, 1–22.
Plangger, K., Campbell, C., Robson, K., & Montecchi, M. (2019). Little rewards, big changes: Using exercise analytics to motivate sustainable changes in physical activity. *Information & Management*, (October), 103216. https://doi.org/10.1016/j.im.2019.103216
Plangger, K., & Montecchi, M. (2020). Thinking beyond privacy calculus: Investigating reactions to customer surveillance. *Journal of Interactive Marketing*, *50*, 32–44. https://doi.org/10.1016/j.intmar.2019.10.004
Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
Prochaska, J. O., Johnson, S., & Lee, P. (2009). The transtheoretical model of behavior change. In S. A. Shumaker, J. K. Ockene, & K. A. Riekert (Eds.), *The Handbook Of Health Behavior Change* (pp. 59–83). Springer Publishing. Retrieved from https://psycnet.apa.org/record/2008-17602-004.
Prochaska, J. O., & Marcus, B. (1994). The transtheoretical model: Applications to exercise. In R. K. Dishman (Ed.), *Advances in exercise adherence* (pp. 161–180). Human Kinetics

Publishers. Retrieved from https://psycnet.apa.org/record/1994-98849-004.
Pyky, R., Koivumaa-Honkanen, H., Leinonen, A. M., Ahola, R., Hirvonen, N., Enwald, H., … Korpelainen, R. (2017). Effect of tailored, gamified, mobile physical activity intervention on life satisfaction and self-rated health in young adolescent men: A population-based, randomized controlled trial (MOPO study). *Computers in Human Behavior*, *72*, 13–22. https://doi.org/10.1016/j.chb.2017.02.032
Radel, R., Pelletier, L., Pjevac, D., & Cheval, B. (2017). The links between self-determined motivations and behavioral automaticity in a variety of real-life behaviors. *Motivation and Emotion*, *41*(4), 443–454. https://doi.org/10.1007/s11031-017-9618-6
Rauschnabel, P. A., Hein, D. W., He, J., Ro, Y. K., Rawashdeh, S., & Krulikowski, B. (2016). Fashion or technology? A fashnology perspective on the perception and adoption of augmented reality smart glasses. *i-com*, *15*(2), 179–194.
Robson, K., Plangger, K., Kietzmann, J. H., McCarthy, I., & Pitt, L. (2015). Is it all a game? Understanding the principles of gamification. *Business Horizons*, *58*(4), 411–420. https://doi.org/10.1016/j.bushor.2015.03.006
Rottensteiner, C., Tolvanen, A., & Laakso, L. (2015). Youth athletes' motivation, perceived competence, and persistence in organized team sports. *Journal of Sport Behavior*, *38*(4), 1–18.
Royer, H., Stehr, M., & Sydnor, J. (2015). Incentives, commitments, and habit formation in exercise: Evidence from a field experiment with workers at a Fortune-500 company. *American Economic Journal: Applied Economics*, *7*(3), 51–84. https://doi.org/10.1257/app.20130327
Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. http://doi.apa.org/journals/amp/55/1/68.html
Segar, M. (2015). *No sweat: How the simple science of motivation can bring you a lifetime of fitness* (1st ed.). Newyork: American Management Association (AMACOM).
Segar, M. L. (2017). Activity tracking + motivation science: Allies to keep people moving for a lifetime. *ACSM's Health & Fitness Journal*, *21*(4), 8–17.
Soni, M., Jain, K., & Jajodia, I. (2021). Mobile health (mHealth) application loyalty in young consumers. *Young Consumers*, *22*(3), 429–455.
Srivastava, S., & Shainesh, G. (2015). Bridging the service divide through digitally enabled service innovations. *MIS Quarterly*, *39*(1), 245–268.
Statista (2020). *eServices Report 2020 – Fitness*. Retrieved from https://www.statista.com/study/36674/fitness-report/. Accessed January 25, 2021.
Sun, T., & Zhong, B. (2020). Multitasking as multisensory behavior: Revisiting media multitasking in the perspective of media ecology theory. *Computers in Human Behavior*, *104* 106151. https://doi.org/10.1016/j.chb.2019.09.027
Sundel, M., & Sundel, S. (2017). *Behavior change in the human services: Behavioral and cognitive principles and applications* (6th ed.). Sage Publishing.
Teixeira, P. J., Carraça, E. V., Markland, D., Silva, M. N., & Ryan, R. M. (2012). Exercise, physical activity, and self-determination theory: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *9*, 78. https://doi.org/10.1186/1479-5868-9-78
Tu, R., Hsieh, P., & Feng, W. (2019). Walking for fun or for “likes”? The impacts of different gamification orientations of fitness apps on consumers’ physical activities. *Sport*

Management Review, *22*(5), 682–693.
Uetake, K., & Yang, N. (2019). Inspiration from the "biggest loser": Social interactions in a weight loss program. *Marketing Science*, 39(3), 459-665. https://doi.org/10.1287/mksc.2018.1116
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178.
Villalobos-Zúñiga, G., & Cherubini, M. (2020). Apps that motivate: A taxonomy of app features based on self-determination theory. *International Journal of Human-Computer Studies*, *140*, 102449.
Watson, R. T., Pitt, F., Berthon, P., & Zinkhan, G. M. (2002). U-commerce: Expanding the universe of marketing. *Journal of the Academy of Marketing Science*, *30*, 333–347. https://doi.org/10.1177/009207002236909
Weinstein, N., & Przybylski, A. K. (2019). The impacts of motivational framing of technology restrictions on adolescent concealment: Evidence from a preregistered experimental study. *Computers in Human Behavior*, *90*, 170–180. https://doi.org/10.1016/j.chb.2018.08.053
West, J. H., Belvedere, L. M., Andreasen, R., Frandsen, C., Hall, P. C., Crookston, B. T. (2017). Controlling your "app" etite: How diet and nutrition-related mobile apps lead to behavior change. *JMIR Mhealth Uhealth*, *5*(7) e95. https://doi.org/10.2196/mhealth.7410
World Health Organization (2017). *WHO | 10 facts on obesity.* Retrieved from https://www.who.int/features/factfiles/obesity/en/. Accessed March 26, 2020.
World Health Organization (2018). *Physical activity.* Retrieved from http://www.who.int/news-room/fact-sheets/detail/physical-activity. Accessed August 28, 2018.
Wu, L. H., Wu, L. C., & Chang, S. C. (2016). Exploring consumers' intention to accept smartwatch. *Computers in Human Behavior*, *64*, 383–392. https://doi.org/10.1016/j.chb.2016.07.005

Appendix

Table A.1

Other Measures Utilized

Habitual Use (Adapted from Venkatesh et al., 2012)	1. The use of X has become a habit for me. 2. I am addicted to using X. 3. I must use X. 4. I do not want to do physical activities without my X.
Autonomous Regulation Index (RAI) (Adapted from Rottensteiner et al., 2015)	1. Because people around me reward me when I do. 2. Because it gives me pleasure to learn more about my sport. 3. Because I would feel bad about myself if I did not take the time to do it. 4. Because practicing sports reflects the essence of who I am. 5. Because through sport, I am living in line with my deepest principles. 6. Because I think others would disapprove of me if I did not. 7. Because it is interesting to learn how I can improve. 8. Because it is one of the best ways that I have chosen to develop other aspects of myself. 9. Because I have chosen this sport as a way to develop myself. 10. Because I feel better about myself when I do. 11. Because I find it enjoyable to discover new performance strategies. 12. Because I would not feel worthwhile if I did not. 13. Because participating in sport is an integral part of my life. 14. Because people I care about would be upset with me if I didn't. 15. Because I have found it is a good way to develop aspects of myself that I value.

Table A.2

Construct Reliability and Validity Scores

Scale Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
gaming	0.813	0.817	0.814	0.523
instructing	0.827	0.829	0.828	0.547
sharing	0.869	0.869	0.869	0.624
tracking	0.781	0.781	0.781	0.471

Table A.3

Factor Loadings

Item	gaming	instructing	sharing	tracking
gaming1	0.637			
gaming2	0.704			
gaming3	0.574			
gaming4	0.733			
instructing1		0.729		
instructing2		0.526		
instructing3		0.740		
instructing4		0.676		
sharing1			0.798	
sharing2			0.796	
sharing3			0.819	
sharing4			0.746	
tracking1				0.750
tracking2				0.836
tracking3				0.647
tracking4				0.579

Note: We conducted the analysis by excluding Gaming 3, Instructing 2, and Tracking 4, and we did not observe any significant differences in the results.

Table A.4

Outer VIF Values for Collinearity

Item	VIF
gaming1	1.528
gaming2	1.778
gaming3	1.572
gaming4	2.021
instructing1	1.480
instructing 2	2.480
instructing 3	2.201
instructing 4	1.636
sharing1	2.048
sharing2	2.110
sharing3	2.341
sharing4	1.971
tracking1	1.617
tracking2	1.734
tracking3	1.587
tracking4	1.468