Journal of Health Communication, 00: 1–7, 2017

ISSN: 1081-0730 print/1087-0415 online
DOI: https://doi.org/10.1080/10810730.2017.1382617

Routledge
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"Social Networkout": Connecting Social Features of Wearable Fitness Trackers with Physical Exercise

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Despite widespread understanding of the benefits of physical activity, many adults in the United States do not meet recommended exercise guidelines. Burgeoning technologies, including wearable fitness trackers (e.g., Fitbit, Apple watch), bring new opportunities to influence physical activity by encouraging users to track and share physical activity data and compete against their peers. However, research has not explored the social processes that mediate the relationship between the use of wearable fitness trackers and intention to exercise. In this study, we applied the Theory of Planned Behavior (Ajzen, 1991) to explore the effects of two communicative features of wearable fitness devices—social sharing and social competing—on individuals' intention to exercise. Drawing upon surveys from 238 wearable fitness tracker users, we found that the relationship between the two communication features (social sharing and competing) and exercise intention was mediated by attitudes, subjective norms, and perceived behavioral control. The results suggest that the ways in which exercise data are shared significantly influence the exercise intentions, and these intentions are mediated by individuals' evaluation of exercise, belief about important others' approval of exercise, and perceived control upon exercise.

Being physically active is one of the most important predictors of physical and mental health (Centers for Disease Control and Prevention, 2015). Research has shown that 30 minutes of daily, moderate-intensity physical activity can significantly reduce the risk of a variety of chronic diseases, including cardiovascular disease, type 2 diabetes, and some cancers, as well as enhance mental health and well-being (Reiner, Niermann, Jekauc, & Woll, 2013). However, even though people are aware of the benefits of physical activity, most do not meet the Centers for Disease Control and Prevention's physical activity guidelines (Lee et al., 2012).

Given the disconnect between knowing the benefits of physical exercise and actual exercise engagement, the advents of wearable fitness trackers (e.g., Fitbit, Apple watch, Garmin) and social media sites (e.g., Facebook, Twitter, Instagram) have brought about an opportunity to influence physical exercise by encouraging people to track and share fitness data online, engage in friendly exercise competitions, and build active communities (Epstein, Jacobson, Bales, McDonald, & Munson, 2015; Shih, Han, Poole, Rosson, & Carroll, 2015). Wearable fitness trackers typically operate in tandem with social media tools that generate suggested narrative posts and associated numerical data, such as maps of runs or calories burned that users can share as status updates (Harrison, Marshall, Bianchi-Berthouze, & Bird, 2015; Munson & Consolvo, 2012). Some wearable fitness trackers, such as Fitbit, also allow users to compete with others through a "leaderboard," which shows the visual details of competitions (Fritz, Huang, Murphy, & Zimmermann, 2014). Users can potentially benefit by sharing their data and receiving encouragement, support, recommendations, and feedback from family members, friends, coworkers, and even training experts (Kreitzberg, Dailey, Vogt, Robinson, & Zhu, 2016; Munson, Cavusoglu, Frisch, & Fels, 2013). This integration of fitness tracking and social media use makes wearable devices a promising intervention platform for benefiting users' physical activity.

Despite this promising technology, research has yet to examine the effects of these social features in wearable fitness trackers. To address this research gap, the current study applies the Theory of Planned Behavior (Ajzen, 1991) to explore the effects of two features—social sharing and social competing—on intention to exercise. Understanding the mechanism of how social sharing and social competing affect people's intention to exercise is an important and timely concern, as the market for wearable technology, including Fitbit, Apple watch, and others, continues to grow rapidly. With the popularity of wearable fitness trackers expanding, research that explores the influence of wearable device use could shed light on future health interventions.

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Literature Review

Wearable Fitness Trackers, Social Sharing, and Social Competing

Wearable fitness trackers can be broadly classified as a persuasive technology designed to change attitudes or behaviors of users through persuasion and social influence, rather than coercion (Fogg, 2003). Fogg (2003) provided a framework for understanding the role of wearable fitness trackers in health behavior change: as tools, media, and social actors. First, as a tool, wearable fitness trackers use various types of sensors to provide data about users' physical activities such as steps taken, distance traveled, and calories burned (Munson & Consolvo, 2012). This form of automated data gathering and presenting allows users to track their physical activity as well as obtain insights into their daily behaviors and health status (Harrison et al., 2015). Second, as a medium, wearable fitness trackers encourage individuals to increase their physical activity by notifying them of their performance levels and helping them to set new goals (Fritz et al., 2014). For example, the Fitbit system sets benchmarks for step counts, calories burned, flights climbed, active minutes, and distance traveled each day. As the user begins to beat their goals on a regular basis, Fitbit suggests that they raise the bar. Third, as a social actor, wearable fitness trackers can be persuasive by rewarding people with positive feedback, modeling a target behavior or attitude, and providing a support network (Shih et al., 2015). Collectively, wearable fitness trackers produce a trend of increased personal health monitoring and social connectedness.

In this study, we focus on the social-actor mechanism of health behavior change by exploring the effects of the two social features of wearable fitness devices: social sharing and social competing. More particularly, we define *social sharing* as the act of disclosing tracking data and exercise via social media, while referring to *social competing* as the effort of engaging in competitions on social media using tracking data. Over the years, rooted in the notion of self-disclosure—"the act of revealing personal information to others" (Jourard, 1971, p. 2)—social sharing has been widely integrated into self-tracking tools (Epstein, Borning, & Fogarty, 2013), and even when sharing has not been technically supported, users of wearable fitness trackers have found other ways to share their data (Choe, Lee, Lee, Pratt, & Kientz, 2014). Social sharing allows individuals to disclose fitness data (e.g., distance, heart rate) or feelings about physical exercise (e.g., pleasant, unenjoyable) to a whole network of "friends" or followers, composed of large and diverse audiences (Gilbert & Karahalios, 2009).

In addition to social sharing, the social competing aspect of wearable fitness trackers tap into people's competitive spirit by bringing in the presence of others, which may keep people committed to their goals and have a positive impact for physical exercise (Kreitzberg et al., 2016). Theories of social facilitation (Zajonc, 1965) and social comparison (Festinger, 1954) have long since been used to explain changes in exercise behavior when in the presence of others. Studies have suggested that social presence causes individuals to evaluate and adjust their exercise, and this change can result from assessing themselves through comparison with others (Strauss, 2002). For example, Fitbit has successfully implemented social competing with their "leaderboard," which ranks users against others in their social networks by their weekly step count or calories burned. It also allows people to communicate with (e.g., cheer or taunt) each other in the process. This simple functionality holds the potential for making the device much more effective as well as addictive, motivating users to exercise for the sake of improving their rankings (Munson et al., 2013). In order to explore the effects of social sharing and social competing on people's physical activity, we now turn to the theoretical constructs of Theory of Planned Behavior.

Theory of Planned Behavior

The Theory of Planned Behavior (TPB) suggests that the proximal determinant of behavior is one's intention to engage in that behavior (Fishbein & Ajzen, 2010). According to the theory, attitude, subjective norm, and perceived behavioral control jointly predict behavioral intention. Subsequently, intention predicts one's behavior (Ajzen, 1991). Within the context of physical exercise, attitude refers to the degree to which an individual has a favorable evaluation of exercising. Subjective norm is the belief about whether important (referent) others in an individual's life approve or disapprove of exercise, and the perceived social pressure to comply with those people. Perceived behavioral control refers to the extent to which an individual believes that they are capable of exercising, and whether they perceive that they are, or are not in control of exercising.

In this study, we propose that social sharing and social competing have an indirect effect on people's intention to exercise through directly predicting TPB variables. More specifically, we assert that if social sharing and social competing matter to exercise, then the mechanism of that effect may reflect any or all of three mechanisms: acquisition of attitudinal information, normative formation and reinforcement, or reminding of capacity and autonomy. First, social sharing and social competing may increase the probability of exposure to and recall of attitudinal information describing some degree of favorableness or unfavorableness to exercise. Information attended to during social sharing and social competing may describe emotions and drive generated by exercise, cognitive consideration of the extent to which engaging in physical exercise would be advantageous, or even instructions for successful exercise routine.

Second, social sharing and social competing may form, develop, or reinforce normative beliefs that most others engage in exercise and/or that exercise is expected. This process may encourage exercise by social influence and peer pressure and meet people's intrinsic need for personal connection with others (e.g., feeling part of a workout group or weight loss program). Finally, social sharing and social competing may remind a person of his or her exercise capability and autonomy of making independent decisions to exercise. Importantly, this process may make the reasons of exercise more cognitively accessible when making decisions to exercise or not. In sum, by directly influencing attitude, subjective norm, and perceived behavioral control, the social features of wearable fitness trackers provide a promising yet under-researched opportunity for understanding people's intention to exercise. Hence, the following hypothesis is proposed:

H1: Attitudes toward physical activity, subjective norms regarding physical activity, and perceptions of control regarding physical activity mediate the relationship between social sharing and social competing and an individual's intention to physically exercise.

Method

Participants and Procedure

To participate in the study, participants were required to be at least 18 years old, own a wearable fitness tracker, and speak English. Following Institutional Review Board approval, we recruited participants in two ways in order to obtain a diverse sample. First, a random sample of 1149 employees at a local branch of a large, worldwide technology company based in the southwestern United States were invited to complete a questionnaire about their use of fitness trackers. This company recently handed out free Fitbit fitness trackers to employees as part of a workplace health promotion initiative. The researchers drafted an email, which included a brief description of the study and its criteria, an invitation to participate, and a link to the online questionnaire. A senior manager at the company forwarded the email to employees. Among these employees, 148 completed the survey, representing a 12.9% response rate.

Second, students in a communication course at a large university in the southwestern United States were asked to each recruit three eligible people to participate in the study. The researchers emailed students a brief description of the study and its criteria, an invitation to solicit friends and family who owned fitness trackers to participate in the research, and a link to the online questionnaire. Students who recruited three participants were offered extra credit, and 70% of students recruited participants ($n = 90$) for the study.

Through recruiting participants in these two ways, we received a total of 238 usable responses. In the sample, the participants were 72% ($n = 171$) male. The mean age of the participants was 30.2 years old ($SD = 6.2$), and the average educational level is college degree (37.3% had a high school degree, 31.5% had a bachelor's degree, 25.08% held a master's degree, and 6.27% had a doctoral degree). Of the participants, 42.4% ($n = 99$) were Asian, 40.1% ($n = 95$) Caucasian, 11.3% ($n = 27$) Hispanic or Latino, and 7 African American ($n = 2.9\%$). Notably, we conducted a series of t-tests to examine the difference between the two ways of recruiting participants. The results revealed that there were no significant differences ($p < .05$) between the two samples with respect to major variables—including social sharing, social competing, attitudes, subjective norms, perceived behavioral control, and intention to exercise. To further validate this finding, we performed a series of configural and metric invariance tests using confirmatory factor analysis (CFA) and confirmed that the two groups were invariant among major variables proposed in the mediation model.

Measures

Unless otherwise noted, all Likert-based variables were rated on 7-point scales with the anchors *Strongly Disagree* (1) and *Strongly Agree* (7).

Social Sharing

Social sharing captures individuals' likelihood to engage in online communication behaviors about fitness data sharing. To construct this measure, we created a series of items assessing wearable fitness tracker users' engagement in fitness data sharing with their connections on social media (e.g., Facebook, Twitter, Instagram, etc.). The instrument included items asking about participants' sharing behaviors (e.g., I upload my fitness data on social media, leaderboard, or other mobile fitness app) and social networking (e.g., I comment under others' update regarding fitness data). To ensure the validity of the instrument, we conducted an exploratory factor analysis on the seven items using principal component analysis with Varimax rotation. After removing cross-loading items, the remaining items loaded clearly onto one, five-item factor. The CFA confirmed that the model including the five items was a good fit to the data. These items had $M = 5.17$, $SD = 0.92$, and a Cronbach's $\alpha = .91$.

Social Competing

A seven-item measure was created for this study to ask specifically about employees' engagement in online competing activities using fitness data. This instrument captures actual competitive behaviors (e.g., I compete with others for steps using social media, leaderboard, or other mobile fitness app) as well as competitive motivations (e.g., I feel left behind if I do not accomplish the team challenge goal). To validate the measure, we conducted an exploratory factor analysis on the seven items using principal components analysis with Varimax rotation, and the outcome indicated that all items loaded clearly onto one, seven-item factor. A following CFA suggested that the model including the seven items was a good fit to the data. These items had good reliability ($\alpha = .95$) and resulted in a scale with $M = 5.44$, $SD = 1.33$. Items, means, and standard deviations for the measure of social sharing and social competing are presented in Table 1.

Attitude

Individuals' attitude toward physical exercise was measured using a series of questions adapted from Okun and colleagues' (2002) study on individual's attitude on leisure time physical activity. This set of items was also validated by other studies (e.g., Zhang et al., 2015). In this study, participants were asked on semantic differential items from 1 to 7 to rate "To me participating in physical exercise is:" *harmful* (1) to *beneficial* (7); *useless* (1) to *useful* (7); *weak* (1) to *strong* (7); *passive* (1) to *active* (7); *foolish* (1) to *wise* (7); *boring* (1) to *interesting* (7); *unenjoyable* (1) to *enjoyable* (7); *unpleasant* (1) to *pleasant* (7); *bad* (1) to *good* (7); and undesirable (1) to desirable (7). These items demonstrated strong reliability: $\alpha = .90$, $M = 5.05$, $SD = 0.88$. Larger values indicate more favorable attitudes toward physical exercise.

Table 1. Means and standard deviations for social sharing (SS) and social competing (SC)

Items[a]	*M*	*SD*
SS1. I upload my fitness data (e.g., steps, miles, and running trajectory) on social media, leaderboard, or other mobile fitness app.	5.25	0.79
SS2. I comment under others' update regarding fitness data.	4.20	0.91
SS3. I tend to share my physical activity using social media, leaderboard, or other mobile fitness app.	4.15	0.81
SS4. I volunteer to inform others about the benefit of using fitness trackers on social media, leaderboard, or other mobile fitness app.	4.06	0.99
SS5. I share about the benefits I experience from using my fitness tracker on social media, leaderboard, or other mobile fitness app.	5.17	0.90
SC1. I compete with others for steps using social media.	4.22	0.72
SC2. I engage in friendly competition with friends, family, coworkers, or anyone else using wearable fitness trackers.	4.48	0.64
SC3. I feel left behind if I do not accomplish the team challenge goal.	4.03	0.66
SC4. I am motivated by competition with others.	5.58	0.48
SC5. I feel a great sense of achievement when I complete competitive goals and receive achievements and badges.	5.05	0.59

[a] Scale ranges from 1 = *strongly disagree* to 7 = *strongly agree*

Subjective Norms

The three-item measure of subjective norms was adapted from Courneya, Conner, and Rhodes's (2006) study on TPB in the exercise domain. Participants were asked to respond to the question, "I think that if I were to participate in physical exercise over the next month, my contacts on social media, leaderboard or other fitness apps would be…" on three semantic differential items: *disapproving* (1) to *approving* (7), *unsupportive* (1) to *supportive* (7), and *discouraging* (1) to *encouraging* (7). These items demonstrated strong reliability: α = .93, *M* = 6.03, *SD* = 0.93. Larger values represent more favorable subjective norms toward physical exercise.

Perceived Behavioral Control

The perceived behavioral control measure was adapted from Sallis and colleagues' (1988) scale on measuring perceived behavioral control in relation to performing physical exercise. A sample item reads, "I stick to my exercise program when I am busy." These items had good reliability (α = .88) and resulted in a scale with *M* = 4.78, *SD* = 0.68.

Behavioral Intention

Behavioral intention was measured by adapting the scale developed by Courneya et al. (2006). Participants were asked to answer the following three questions: How motivated are you to participate in physical activity over the next month? (1 = *not at all motivated*, 7 = *extremely motivated*); How strongly do you intend to do everything you can to participate in any physical activity over the next month? (1 = *do not intend*, 7 = *strongly intend*); How committed are you to doing any physical activity over the next month? (1 = *not at all committed*, 7 = *completely committed*). These items created a reliable measure: α = .92, *M* = 4.49, *SD* = 1.08.

Control Variables

The control variables age, gender, and educational level were consecutively modeled. All the parameters presented in the final model held true when controlling for these variables. This outcome indicates that the control variables had no influence on the overall findings; thus, we excluded these variables from the final model for reasons of parsimony.

Results

The hypothesis was tested using structural equation modeling (SEM) in Mplus (Version 7). Prior to the tests, descriptive and frequency analyses were performed to inspect skewness and kurtosis. The results indicated that all variables were normally distributed. Descriptive statistics and zero-order correlation coefficients are presented in Table 2.

Test for Mediation

Mediation analyses were completed using SEM with bootstrapping methods (Hayes, 2013). Following the recommendation of good fit by Hu and Bentler (1999), model fit was evaluated using the maximum likelihood chi-squared statistic, comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). They further suggest the joint criteria to retain a good structural testing model: CFI ≥ .96 and SRMR ≤ .10, or RMSEA ≤ .06 and SRMR ≤ .10. All path coefficients were reported as standardized estimates (see Figure 1).

We validated the factor structure of the model using CFA. Our initial measurement model with unit-loading indicators to scale latent constructs indicates a good model fit: χ^2 (26) = 102.64, *p* = . 03, CFI = .95, TLI = .97, RMSEA = .01, and SRMR = .02. Neither of the cross-loadings of one measurement item over multiple constructs nor low-factor loadings were found to compromise the overall model fit.

Following CFA, SEM analysis was used to test the structural model. The results revealed that the structural model was a good fit to the data: χ^2 (7) = 435.06, *p* = .17, CFI = .94, TLI = .98, RMSEA = .04, and SRMR = .05. The complete model, shown in Figure 1, shows support for H1. There was a significant indirect effect of social sharing on intention to exercise through attitudes (b^* = 0.127, BCa CI: .037, .221, $p < .001$), subjective norms (b^* = 0.093, BCa CI: .037, .154, $p < .01$), and perceived behavioral control (b^* = 0.112, BCa CI: .075, .159, $p < .01$). Similarly, There was a significant indirect effect of social competing on intention to exercise through attitudes (b^* = 0.091, BCa CI: .013, .134, $p < .01$), subjective norms (b^* = 0.040, BCa CI: .037, .044, $p < .05$), and perceived behavioral control (b^* = 0.104, BCa CI: .056, .163, $p < .01$).

Table 2. Means, standard deviations, and correlations

Variable	*M*	*SD*	1	2	3	4	5	6
1. Social sharing	5.17	0.92						
2. Social competing	5.44	1.33	0.82**					
3. Attitude	5.05	0.88	0.26**	0.43**				
4. Subjective norms	6.03	0.93	0.29**	0.44**	0.71**			
5. Perceived behavioral control	4.78	0.68	0.65**	0.62**	0.53**	0.41**		
6. Behavioral intention	4.49	1.08	0.52**	0.58**	0.49**	0.39**	0.83**	

*$p \leq .05$. **$p \leq .01$.

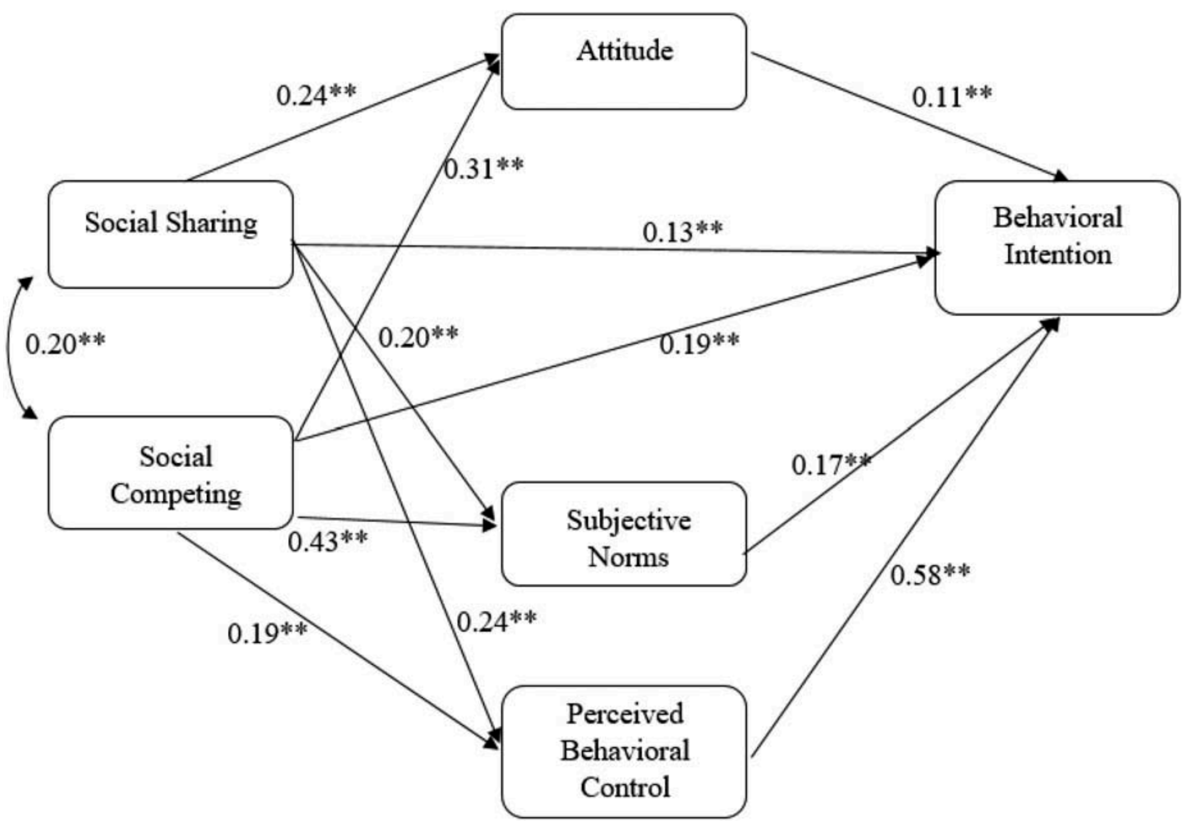

Fig. 1. Path coefficients for the mediation model. *$p \leq .05$. **$p \leq .01$. ***$p \leq .001$.

Discussion

With the growing number of people wearing fitness trackers, it is important to understand the role of these devices in changing exercise intentions. The TPB is a useful framework in predicting individuals' intentions to exercise (Conner & Sparks, 2005), along with a variety of other health behaviors (e.g., Freberg, 2013). However, our findings suggest that two communicative features of wearable devices—social sharing and social competing—offer an expanded perspective as information and communication technologies are transforming patterns of health communication. The current study demonstrates that attitudes, subjective norms, and perceived behavioral control mediate the relationship between social sharing and social competing and an individual's intention to exercise.

This study contributes to health communication in several ways. First, this study uses TPB to account for the communicative concepts of social sharing and social competing in the era of "computer-mediated communication" or any human communication that occurs through the use of two or more electronic devices (Walther, 2011). Ajzen (1991) has noted that other factors might influence behavior, suggesting that further research determine if there are components that could be added to the theory to make it a better model of behavior. With the growing role technology plays in individuals' lives, it follows that such devices might influence behavior in new ways. Indeed, the current study demonstrates that technological devices' social features influence people's intention to exercise. As suggested by Fishbein and

Ajzen (2010), the proposed mediation model can be used as a framework for developing and evaluating behavior change interventions. For example, if we know that people are more likely to exercise if they share their health data, then future health campaigns and fitness devices can be sure to include these features to more effectively change behavior.

Second, we examined TPB in the context of wearable fitness trackers, because social sharing and social competing are two communicative features inherent to these devices. However, this study may contribute to more than just research on fitness devices. Because so much of our everyday behaviors are shared and communicated with others through social media, social sharing and social competing may also play a role in predicting exercise behaviors, even for those who are not active fitness device users. Individuals without wearable fitness trackers may still share comments about their workouts via social media, and findings of the current study would suggest that such posts would potentially influence intentions to exercise. Thus, although this extended model was developed and shaped in the context of wearable fitness trackers, these findings may have implications beyond the use of such devices.

Third, the current study highlights the importance of social sharing and social competing in health communication, two important communication variables that are under-explored in current research. We encourage subsequent studies to further explore social sharing and social competing in health and other applied contexts, and we hope that the valid measures developed for this study will serve as useful instruments for future research. Apart from these implications for research, this study offers several practical benefits as well.

Practical Implications

The current study highlights important communicative features that should continue to be incorporated into wearable fitness devices in order to promote physical activity (Epstein et al., 2015). Although most devices currently include social sharing and social competing functions, this research demonstrates the importance of maintaining devices' compatibility with social media. Designers should consider ways to easily share fitness data and create various competitions to help users engage with others.

Along these lines, other health-related products and health campaigns might make use of our findings, seeking to incorporate social sharing and social competing with an array of mediated messages in multiple channels for addressing important problems (e.g., smoking, binge drinking, AIDS, drug use, and heart disease). For example, antismoking campaigns could encourage people to share images of themselves wearing nicotine patches or count and share how many smoke-free days they have completed. Campaigns and health-related products could also create social media apps and sites where users can compete with others, perhaps for the number of vegetables a family has eaten in the month or how many members of a family got their flu vaccine. Just as these communicative concepts predict health behaviors in the context of wearable fitness trackers, these gamification strategies may also play a role shaping in other behavioral intentions.

Finally, this study has implications for workplace health promotion initiatives. Although not all companies offer free wearable fitness trackers to their employees, over half of all employers with 50 or more employees now offer a wellness program (Mattke et al., 2013). Such programs often include physical exercise classes, nutrition training, health information screening and education, and occupational health services (Farrell & Geist-Martin, 2005). Unfortunately, prior research has found that employees' participation levels in workplace health promotion programs are typically below 50% (Robroek, Van Lenthe, Van Empelen, & Burdorf, 2009). Although communication scholars have suggested that understanding employees' health identities and increasing their sense of belongingness could boost employees' participation (Dailey & Zhu, 2016), this study sheds light on the key role of social sharing and social competing in shaping individuals' involvement in physical activity. By incorporating these communication features into such programs, organizations may have greater success at garnering employee participation in wellness initiatives.

Limitations and Directions for Future Research

Although the current study offers several theoretical and practical contributions, there are several limitations that should be considered when interpreting the findings. With regard to measurement, we did not control the length of wearable ownership, which could potentially affect individuals' social sharing and social competing behaviors. Similarly, this study failed to consider the differences in physical characteristics, types of activities and lifestyle, and unique affordances of devices. All of those factors may contribute to individuals' perceptions on social sharing and social competing. We also did not ask participants the extent to which they personally knew the individuals with whom they were socially sharing or competing. Depending on the level of interaction and communication with others outside of fitness tracking devices, social sharing and social competing may influence exercise intentions differently. In addition, we only measured behavioral intentions, not actual health behaviors. Future studies should look at the effects of social sharing and social competing on actual health tracker data, rather than health perceptions or intentions.

Methodologically, SEM cannot test directionality in relationships, so future studies should explore whether people with a greater intent to exercise feel more comfortable with social sharing and social competing. Furthermore, subsequent research should test the influence of social features within wearable devices through experimental design using nationally representative data. In a future study, researchers could randomly assign half of participants to a control group, who wear fitness trackers without social sharing and social competing features to test the effects of these communicative concepts on physical activity. Future research should also seek to understand if social sharing or social competing is more effective in changing behaviors. Moreover, to influence individuals who currently do not intend to perform physical activity requires formative research to identify the primary behavioral, normative, and control beliefs that can be targeted in inventions informed by social sharing and social competing. Finally, longitudinal data would be useful to explore physical activity changes over time. Wearable fitness trackers offer the unique opportunity to collect intensive context- and time-dependent (longitudinal) data and incorporate communication feedback loops (response/reaction), which enables researchers to test various theoretical concepts and dynamic models that underlie them.

In conclusion, the current study provides a more comprehensive understanding of TPB by showing that attitudes, subjective norms, and perceived behavioral control mediate the relationship between social sharing and social competing and an individual's intention to physically exercise. In addition to providing a fuller picture of how wearable fitness trackers influence health intentions, findings from this research may be applied to other health-related products and campaigns. With the growth of social media, communication scholars and practitioners can better understand and change health behaviors by focusing more on the communicative features that may be embedded into health devices and initiatives.

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