Investigating the Role of Personalized Feedback from Smart Wearable Devices—Leveraging Individual Psychological Dimension

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Abstract

This study centers on how smart wearable devices influence individuals who engage in physical activity, with a focus on the moderating effects of social interaction and psychological factors. First, analyses of variance revealed that people who use smart wearables perform significantly better in health-related behaviors compared to non-users. The study examines the dimension of social interaction, divided into “social connectedness” and “social assurance.” Both factors are shown to moderate the relationship between device usage and health behaviors. In other words, individuals who feel stronger social connectedness or assurance are more likely to see better health outcomes from wearing these devices. Finally, regarding psychological factors, the study focuses on “personal capability” and “acceptance of self and life.” Again, both sub-dimensions significantly moderate the effect of wearable device use on health behaviors. Individuals with higher levels of personal capability and self-acceptance experience greater improvements—indicating that self-efficacy, optimism, and a growth mindset can magnify the advantages offered by technological feedback. Overall, this research confirms that smart wearables do hold substantial potential for promoting healthier behaviors. Yet, their effectiveness depends on a holistic ecosystem that combines social support (social interaction) and individual psychological strength (personal capability and self-acceptance). For future research, longer-term longitudinal studies or mixed-methods approaches are recommended to examine how cultural contexts and various psychological or social conditions influence both the continued use of wearables and the resulting outcomes.

Keywords: smart wearable devices, health behavior, social interaction, psychological factors

Introduction

From a sports science perspective, there is a growing emphasis on leveraging objective data to plan training regimens and evaluate performance. Professional sports teams frequently rely on various sensors and scientific equipment to analyze athletes' physical status and refine performance strategies, especially in high-stakes competitive environments. This trend has gradually extended to the general public, many of whom now appreciate the concept of "scientific exercise," using smart devices to increase workout efficiency or reduce the risk of injury. In parallel, sports psychology explores how both intrinsic and extrinsic motivations such as self-efficacy, goal-setting, social support, and the need for achievement influence exercise participation. By offering real-time feedback, interim goals, and social networking features, smart wearables may positively boost exercise motivation. However, if the data analyses or feedback mechanisms of these devices are poorly designed, users could experience anxiety, develop an unhealthy dependence on performance metrics, or become excessively fixated on their numbers. The intricate interplay of such psychological factors warrants deeper investigation.

Today's exercise landscape is remarkably diverse, with participants of all ages, professions, and backgrounds engaging in different forms of physical activity, each with its own set of objectives. From leisurely walks to high-intensity strength training, or from casual jogging to triathlon competitions, each activity involves unique demands and motivations. High-intensity or specialized athletes often prioritize precise data analytics and expert guidance, while more casual exercisers value social features and user-friendly designs. To accommodate both novice and advanced users, smart wearables need to address a variety of needs and preferences. Against this backdrop, these devices have become increasingly central to the world of sports and health promotion—serving both cutting-edge athletic science and the ordinary routines of everyday life. Yet many areas still require deeper examination, including long-term user engagement, how social connections influence exercise motivation, the accuracy of device-generated data, users' psychological experiences, and the tangible health and fitness benefits that emerge over time.

Although numerous studies highlight the positive effects of wearable devices on users' exercise frequency and adherence to healthier behaviors, most of these findings come from short-term observations or single-session experimental designs. Relatively little research has probed the dynamic processes of behavior change that occur over longer periods of use. In addition, some studies note that while people are initially excited by the novelty or data-tracking aspects of a new wearable, they may lose interest or abandon the device over time. This discrepancy may stem from a complex mix of personal factors, such as the type of motivation or attitudes toward technology social influences like support from friends or belonging to a group, and design elements related to user interface and practical functionality. To better understand these interconnected mechanisms, a more extended perspective on how wearable devices shape exercise behaviors is needed, taking into account motivation, habit formation, and the role of social support.

Traditional research often treats the exercising population as a relatively uniform group. In reality, it encompasses a wide spectrum of individuals: professional athletes, amateur runners, gym enthusiasts, older adults, rehabilitation patients, adolescents, and more. Their needs and expectations for wearable devices can differ drastically—where a professional athlete seeks precise metrics and highly specialized training tips, a casual fitness buff may care more about convenience and social features. Older adults and individuals in rehabilitation may require simpler interfaces or safety-monitoring tools. Overlooking such variations makes it difficult to evaluate the real-world impact of smart wearables on different user segments. By considering a broader range of participants in this study, we aim to offer insights that could guide more targeted recommendations.

In business practice, major tech brands are racing to develop more intelligent and user-friendly wearables, investing heavily in marketing and service upgrades. Academia, meanwhile, has focused on assessing the efficacy of these devices and measuring user satisfaction. However, large-scale usage data owned by commercial entities often remains private due to concerns over user privacy or competitive advantage, and academic research may lack sufficient long-term or large-sample datasets to accurately reflect market realities and user needs. This gap between academic research and industry practice makes it challenging to form a well-rounded understanding of how smart wearables truly affect exercise behavior over time. As a result, we still lack robust strategies to encourage sustained use of these devices and reap broader health benefits. By conducting this research, we hope to bridge the academic-practice divide and offer more in-depth, actionable insights.

In summary, the rise of smart wearable devices is reshaping the sports and fitness landscape. While existing research confirms their advantages in fostering healthier behaviors and improving exercise efficiency, there remain critical gaps concerning long-term user motivation, personal and situational differences, objective evaluations of health and fitness outcomes, the complexity of psychosocial interactions, and cross-disciplinary research collaborations. Through deeper empirical investigation and theoretical exploration, we can gain a more comprehensive understanding of how wearable devices fit into the daily lives of exercise participants. This understanding, in turn, will enable us to provide more informed recommendations for technology developers, sports coaches, public health agencies, and consumers themselves—helping all stakeholders make the most of these technologies and the value they bring.

Literature Review

Factors Influencing the Impact of Smart Wearable Devices

Research by Enjeti et al. (2022) showed that while many users experience an initial surge in physical activity due to the novelty of wearable devices or the excitement of setting fitness goals, the ability to maintain these habits over time depends on external support (e.g., social interaction) and the depth of one's health awareness. Similarly, Piwek et al. (2016) concluded that although consumer-grade wearables can boost activity in the early stages—thanks to their ease of use and broad accessibility—users often need additional strategies in the later “post-adoption” phase, such as robust privacy safeguards, cross-platform integration, and partnerships with medical or fitness professionals, to sustain meaningful long-term health benefits. Hartman et al. (2022) provided evidence that wearable activity trackers can serve as effective behavior-maintenance tools if supported by appropriate social features and engagement strategies. Their ultimate goal is to help users convert external feedback into intrinsic motivation so they can uphold healthy behaviors even without constant tracking. Becker et al. (2022) noted that participants were often attracted to free devices out of curiosity; however, without ongoing support or personal interest, usage typically declined after a few weeks. When the devices were used in group settings, participants could observe one another's step counts and overall health progress, fostering a supportive and competitive atmosphere that prolonged device use. Mercer et al. (2016) underscored that if wearables fail to offer evolving behavior-change strategies over time, users quickly lose interest. Conversely, a variety of evidence-based Behavior Change Techniques (BCTs) can promote ongoing participation and produce lasting health improvements. Likewise, Brickwood et al. (2019) stressed that while consumer-grade wearables indeed encourage short-term increases in physical activity, extending these gains requires more comprehensive interventions and well-coordinated support systems. Khabiri et al. (2024), through a systematic review, affirmed the potential of wearable technology in managing chronic conditions but emphasized the importance of “patient-provider collaboration” and “psychological support” in the long run, as well as stable measurement accuracy to avoid dropouts. Jain et al. (2021) found that by integrating a smart scale with a mobile app's real-time feedback after each weigh-in, users stayed consistently aware of their weight trends and continued using the technology over a prolonged period. Bianchi et al. (2023) noted that increased health vigilance during global health crises has led people to rely more on devices capable of monitoring temperature or cardiopulmonary function, thus maintaining usage over time. Papadiochou et al. (2024) observed that both regular users and individuals with chronic illnesses typically display short-term improvements in physical activity or healthy behaviors; however, many studies report a gradual decline after six months when no additional interventions are provided. Building on these findings, this study proposes the following hypothesis: H1: Differences in the use of smart wearable devices will have a significant impact on health behaviors.

Social Interaction as a Moderator of the Impact of Smart Wearable Devices on Health Behavior

Larnyo et al. (2022) observed that receiving peer affirmation or widespread social attention initially boosts users' intrinsic motivation to keep wearing their devices and stick to exercise plans. However, an excessive focus on "social attention" can lead users to push their physical limits or develop anxiety. If validation from others fades, they may become resistant to both the device and the exercise routine. Brickwood et al. (2019) emphasize that wearable devices need to account for the degree of social support in a user's community to deliver long-term health benefits. Social interaction can thus serve either as a powerful catalyst or a roadblock to sustained use. Girginov et al. (2020) note that having friends and family track one's daily steps can provide support but may also create a feeling of constant surveillance or "micro-level social pressure," potentially causing users to drop off over time. Wu et al. (2020) found that having friends who also use the same device can foster mutual comparison and encouragement, which increases physical activity. Conversely, in environments, such as workplaces or households that view exercise or data tracking negatively, users might fear being judged as overly fixated on their step counts, which can lead them to abandon the device. Stragier et al. (2016) report that for newcomers, a welcoming community atmosphere can offer positive social support and heighten motivation to use a wearable device. Yet, Lyons et al. (2014) caution that while social features can be a powerful incentive, the absence of mechanisms to cope with negative social interactions may result in user alienation. Alvarez et al. (2022) highlight that individuals with chronic conditions are especially vulnerable to others' comments or judgments, making "social interference″ a significant concern. Koivisto and Hamari (2019) suggest that gamification elements,such as leaderboards, badges, and achievement systems—can enhance positive social comparisons; however, poor design can undermine self-esteem for users who feel like "losers." Sullivan and Lachman (2017) stress the importance of "mild, moderate" social support in encouraging sedentary populations to become more active; overly critical or intrusive monitoring can have the opposite effect. Lastly, Scolere et al. (2024) point out that social interference not only occurs within circles of friends and family but also in the dynamics between healthcare providers and patients, both of which strongly influence users' trust in wearable devices and their long-term adherence. Based on these insights, this study posits the following hypothesis: H2: Social interaction moderates the effect of smart wearable devices on health behavior.

The Psychological Dimension as a Moderator of the Effect of Smart Wearable Devices on Health Behavior

Cheung et al. (2019) point out that placing excessive emphasis on device-generated data may heighten user anxiety; if designers do not balance "detailed information" with reassuring guidance, the result can be a negative psychological impact. Brickwood et al. (2019) indicate that constant reminders of "failure" from a device can prompt self-doubt or defensive reactions, eventually causing individuals to abandon the wearable altogether to avoid emotional distress. Wu et al. (2020) find that when external feedback cannot be converted into intrinsic motivation over time, users may see devices as useless once the novelty wears off; for those with low self-efficacy, the device can become a symbol of "repeated failure," leading to negative emotions. Li et al. (2016) note that despite the potential health benefits of wearables, strong privacy concerns can overshadow perceived advantages, elevating stress and resulting in discontinued use. Hartman et al. (2022) add that while objective data assists in behavior monitoring, overly frequent or poorly timed feedback can overwhelm users mentally, leading to adverse outcomes when anxiety surpasses an individual's tolerance level. Park (2020) argue that a heightened sense of vulnerability might serve as a catalyst for behavior change or lead to an over-monitoring mindset, culminating in increased anxiety and eventual device abandonment when relief does not follow. Sellahewa et al. (2019) observes that more advanced devices often collect increasingly precise biometric data, yet this can intensify fears of "invasive surveillance," rendering even state-of-the-art features underutilized due to heightened anxiety. Kerbage et al. (2024) caution that wearable devices meant to monitor and intervene in mental health may, without proper guidance, cause individuals to hyper-focus on every emotional fluctuation, ultimately exacerbating anxiety. Piwek et al. (2016) emphasize that wearables can collect a wealth of data, but if users find it too complex or irrelevant, they may simply set the devices aside. According to Sullivan and Lachman (2017), individuals who fundamentally believe "I'm just not going to exercise" often react to device prompts with greater resistance and discomfort, rendering these technologies ineffective. Based on these findings, this study proposes the following hypothesis: H3: The psychological dimension moderates the effect of smart wearable devices on health behavior.

Methodology

Research Variables and Dimension Definitions

1. Smart Wearable Devices

In this study, the measurement for the smart wearable device variable is straightforward: whether participants use such devices or not serves as the main indicator.

2. Health Behavior

This study measures health behavior based on the framework proposed by Clina

et al. (2024). The primary dimensions and example survey items are as follows:

a. Vigorous Activity: Examples: running, playing basketball, singles tennis, fast cycling, aerobics, or any activity that makes you "breathe much harder and have a noticeably faster heartbeat." Sample question items: "In the past seven days, on how many days did you engage in vigorous physical activities?"; "On those days, how many minutes per day did you usually spend doing these vigorous activities?"

b. Moderate Activity: Examples: moderate cycling, brisk walking (not including casual strolls, which may be counted under walking), badminton, table tennis, lifting light objects, or relatively strenuous chores like sweeping or mopping. Sample question items: "In the past seven days, on how many days did you engage in moderate-intensity physical activities?"; "On those days, how many minutes per day did you usually spend doing these moderate activities?"

c. Walking: This includes any form of walking—such as commuting to work or school, dog-walking, or leisure walking—provided the session lasts at least 10 consecutive minutes. Sample question items: "In the past seven days, on how many days did you walk for at least 10 minutes at a time?"; "On those days, how many minutes did you usually spend walking?"

d. Sedentary Time: This covers time spent sitting at work or school, during commutes, and leisure activities like watching TV or using mobile devices at home. Sample question item: "Over the past seven days, approximately how many total hours per weekday (workday) did you spend sitting (e.g., at the office, watching TV, reading, or using a computer)?". To calculate total physical activity, the questionnaire responses (number of days × minutes per day) are multiplied by a corresponding MET (Metabolic Equivalent of Task) value. For example, if a respondent performed 30 minutes of vigorous activity on three days in the past week: 3 days×30 minutes×8 MET=720 MET-minutes/week3 \text{ days} \times 30 \text {minutes}\times8\text{MET}=720\text{MET-minutes/week} 3 days×30 minutes ×8 MET=720 MET-minutes/week. The total MET-minutes/week is then derived by adding the results for vigorous, moderate, and walking activities to determine overall activity levels and subsequently assess health behavior.

3. Social Interaction

This study's measure of social interaction adopts the dimensions proposed by Ferrarini and Nelson (2015):

a. Social Connectedness: This refers to whether individuals feel a close, positive bond with a community, peers, or their environment (Javier and Hermosa, 2024). High-quality social interactions often foster a sense of belonging and acceptance. Sample questionnaire items include: "Using smart wearable devices, I often feel distant from others." (reverse-coded); "Using smart wearable devices, I find it hard to fit into any group." (reverse-coded); "With smart wearable devices, I can easily interact and blend in with others."; "In groups that use smart wearable devices, I feel a strong sense of belonging."

b. Social Assurance: This refers to whether individuals believe they can receive support or recognition from others in social interactions. Such a sense of "safety" makes people more willing to reach out and less likely to withdraw due to fear of rejection or awkwardness. Sample questionnaire items include: "When I have problems using a smart wearable device, I believe I can count on friends or relatives for help."; "I doubt that people around me actually care about my needs regarding smart wearable devices." (reverse-coded); "If I speak up, I know someone will be willing to listen to the issues I'm having with a smart wearable device."; "I don't think I can get enough encouragement from others to keep using my smart wearable device." (reverse-coded)

4. Psychological Dimension

This study measures the psychological dimension based on the framework proposed by Cajada et al.(2023):

a. Personal Competence. This sub-dimension highlights confidence, self-efficacy,

b. Independence and strong willpower. Sample questionnaire items include: "When facing difficulties in life, I can rely on my own capabilities to persist."; "I believe I can learn and grow from setbacks."; "I feel that I am in control of most life decisions."; "Even if my surroundings are unfavorable, I can find ways to make progress."; "Every challenge I face makes me more certain of my own abilities." b. Acceptance of Self and Life

This includes having a positive outlook on one's current situation and life journey, as well as acknowledging personal traits and experiences, whether good or bad.

Sample questionnaire items include: "For the most part, I am optimistic about the future."; "I often get stuck dwelling on past failures and can't move on." (reverse-coded); "I can accept imperfections in myself and my life, and keep going."; "I can calmly acknowledge my past mistakes without constantly blaming myself."; "I accept my life as it is now, even though there are many areas for improvement."; "When I encounter something I can't change, I choose to accept it and focus instead on more meaningful goals."

Research Participants

This study targeted the general public in Taiwan for questionnaire distribution, employing a convenience sampling method via physical surveys. A total of 1,000 questionnaires were distributed, and after excluding invalid or incomplete responses, 906 valid questionnaires remained, yielding a 91% effective response rate.

The participant breakdown is as follows:

1. Smart Wearable Device Usage: 463 respondents indicated they use such devices, while 443 do not.
2. Gender: 502 respondents were male, and 404 were female.
3. Age: 257 were under 30 years old, 384 were between 30 and 50, and 265 were over 50.
4. Education Level: 192 had completed high school or below, 511 had a junior college (specialized) degree, and 203 held a graduate degree or higher.
5. Marital Status: 588 were unmarried, and 318 were married.

Data Analysis Methods

After collecting the questionnaire responses, this study utilized SPSS as the primary tool for data analysis. The analytical procedures included factor analysis, reliability analysis, and analysis of variance (ANOVA).

1. Factor Analysis

To confirm the suitability of each measurement scale, the study conducted factor analyses on all scales included in the questionnaire. An orthogonal rotation method was used to identify the optimal factor loadings for each item across different factors.

2. Reliability Analysis

Cronbach's α was employed to evaluate the internal consistency of the factors identified. A higher α indicates stronger inter-item correlations within a factor, signifying greater internal consistency.

3. Cluster Analysis

Cluster analysis was used to categorize participants based on the dimensions of social interaction and psychological factors, ultimately dividing them into high- and low-level groups.

4. Analysis of Variance (ANOVA)

ANOVA was conducted to examine the impact of smart wearable devices. Where significant differences were found, post-hoc tests such as Scheffé's method, the Tukey-Kramer method, or the Bonferroni correction were applied for multiple comparisons.

Empirical Results

(1) Factor Analysis

Table 1 shows the factor analysis results. After applying factor analysis to the Social Interaction scale, two factors emerged:

1. Social Connectedness (eigenvalue = 3.124, α = 0.87)
2. Social Assurance (eigenvalue = 2.615, α = 0.83)

Together, these two factors explained 76.283% of the total variance.

Similarly, the Psychological Dimension scale also yielded two factors:

1. Personal Competence (eigenvalue = 2.471, α = 0.89)
2. Acceptance of Self and Life (eigenvalue = 2.262, α = 0.85)

Combined, these two factors explained 81.544% of the total variance.

Table 1: Factor Analysis Results

Variable	Factor	Eigenvalue	α	Cumulative Explained Variance
Social Interaction	Social Connectedness	3.124	0.87	76.283
	Social Assurance	2.615	0.83	
Psychological Dimension	Personal Competence	2.471	0.89	81.544
	Acceptance of Self & Life	2.262	0.85	

(2) Effect of Smart Wearable Devices on Health Behavior

Using ANOVA to explore whether smart wearable devices influence health behavior, Table 2 shows that individuals who use such devices exhibit better health behaviors compared to those who do not. Therefore, H1 is supported.

Table 2: ANOVA – Effect of Smart Wearable Devices on Health Behavior

Variable	F Value	P Value	Post Hoc Test
Smart Wearable Devices	18.916	0.001**	Use Devices > No Use Devices

Note: $p < 0.01$.

(3) Effect of Smart Wearable Devices and Social Interaction on Health Behavior

ANOVA was also employed to examine how both smart wearable devices and social interaction influence health behavior. Table 3 indicates significant differences across all cross-factor analyses. As shown in Table 4, the interaction of smart wearable devices and social interaction likewise has a significant effect on health behavior. Consequently, H2 is supported.

Table 3: ANOVA – Effect of Smart Wearable Devices and Social Interaction on Health Behavior

Variable		F Value	P Value
Smart Wearable Devices	Social Interaction		
Use Devices	High Social Connectedness>Low Social Connectedness	4.834	0.023*
Use Devices	High Social Assurance>Low Social Assurance	7.588	0.000**
No Use Devices	High Social Connectedness>Low Social Connectedness	6.123	0.000**
No Use Devices	High Social Assurance>Low Social Assurance	8.446	0.000**
Social Interaction	Smart Wearable Devices		
High Social Connectedness	Use Devices > No Use Devices	5.288	0.016*
Low Social Connectedness	Use Devices > No Use Devices	6.884	0.004**
High Social Assurance	Use Devices > No Use Devices	7.963	0.000**
Low Social Assurance	Use Devices > No Use Devices	9.122	0.000**

Note: * $p < 0.05$, ** $p < 0.01$.

Table 4: Moderating Effect of Social Interaction

Variable	F Value	P Value
Smart Wearable Devices * Social Connectedness	23.158	0.000**
Smart Wearable Devices * Social Assurance	27.842	0.000**

Note: * $p < 0.05$, ** $p < 0.01$.

(4) Effect of Smart Wearable Devices and Psychological Dimension on Health Behavior

Finally, ANOVA was used to assess whether smart wearable devices and psychological factors collectively influence health behavior. Table 5 shows significant differences in each cross-factor analysis, and Table 6 demonstrates a significant interaction effect between smart wearable devices and psychological factors on health behavior. Hence, H3 is supported.

Table 5: ANOVA – Effect of Smart Wearable Devices and Psychological Dimension on Health Behavior

Variable		F Value	P Value
Smart Wearable Devices	Psychological Dimension		
Use Devices	High Personal Competence>Low Personal Competence	6.388	0.000**
Use Devices	High Acceptance of Self & Life>Low Acceptance of Self & Life	6.546	0.000**
No Use Devices	High Personal Competence>Low Personal Competence	8.126	0.000**
No Use Devices	High Acceptance of Self & Life>Low Acceptance of Self & Life	7.545	0.000**
Psychological Dimension	Smart Wearable Devices		
High Personal Competence	Use Devices > No Use Devices	9.143	0.000**
Low Personal Competence	Use Devices > No Use Devices	8.584	0.000**
High Acceptance of Self & Life	Use Devices > No Use Devices	7.791	0.000**
Low Acceptance of Self & Life	Use Devices > No Use Devices	9.433	0.000**

Note: $p < 0.01$.

Table 6: Moderating Effect of the Psychological Dimension

Variable	F Value	P Value
Smart Wearable Devices * Personal Competence	33.283	0.000**
Smart Wearable Devices * Acceptance of Self & Life	37.462	0.000**

Note: $p < 0.01$.

Discussion

This study explored (1) the main effect of smart wearable devices on health behavior, as well as (2) the moderating roles of social interaction and (3) psychological factors. The results show significant influences both in terms of single-factor effects and multi-factor interactions. Below, we discuss the theoretical and practical implications of these findings and compare them with previous research.

Influence of Smart Wearable Devices on Health Behavior (H1)

As indicated in Table 2, smart wearable devices exert a clear positive impact on health behavior. According to the ANOVA results ($F = 18.916$, $p < 0.01$), individuals who use wearable devices scored significantly higher on the health behavior scale compared to non-users. These findings confirm that the real-time monitoring and feedback mechanisms found in wearables can boost users' motivation to exercise, eat better, or practice self-management—aligning with a number of studies suggesting that wearable technologies help increase physical activity and encourage healthier habits. The results once again underscore the potential of technology-based interventions in the field of health promotion. Most wearables contain sensors that track steps, heart rate, and sleep quality in real time. Visualizing this data via an app or on the device itself encourages users to monitor their daily activity levels or routines. Upon noticing that their goals are unmet, users typically become more proactive, for example by adding an evening walk or jog to reach a daily step target—creating a "real-time feedback–behavior adjustment" cycle.

Many devices also integrate with mobile apps to enable goal-setting (e.g., 10,000 steps per day) or offer gamified features, such as badges or milestone achievements. Achieving these goals provides positive reinforcement, which reinforces self-efficacy and motivation over time—a concept that aligns well with Self-Determination Theory (SDT), suggesting that external rewards can gradually become internalized, resulting in stable, lasting health behaviors.

Since daily behaviors are continuously recorded and archived, wearables often enhance users' "self-monitoring," which can reduce procrastination or complacency. In contrast, those without wearables lack objective data and may overestimate their exercise levels or maintain default habits simply because they have no concrete information to challenge their assumptions. In this sense, wearable devices serve as both "activity recorders" and "data reminders." Many prior studies have concluded that wearable technologies benefit weight management and the development of long-term exercise habits. The present findings extend these results, showing that even in different cultural or demographic contexts, users of wearable devices typically display higher health behavior indicators. This outcome likely reflects well-established behavior science principles: real-time, objective, and consistent feedback enables people to adjust their actions and establish clear health goals.

Social Interaction as a Moderator of the Effects of Smart Wearable Devices on Health Behavior (H2)

Tables 3 and 4 suggest that social interaction-encompassing both "Social Connectedness" and "Social Assurance"-modulates the impact that smart wearable devices have on health behavior. When these social factors are high, wearables have an even more pronounced positive effect on health habits; conversely, in the absence of devices, individuals with high social connectedness or assurance still exhibit relatively strong health behaviors, though the statistical gap between them and the wearable-user group remains significant.

Social Connectedness refers to a sense of belonging and mutual trust with one's social circle, friends, or family. When people have strong social ties, they are more inclined to undertake healthy activities together—such as jogging or sharing their daily routines—especially if they also use a wearable device. The data here implies that people high in social connectedness gain additional benefits from wearables, likely because they actively use apps and community features to interact, compete, and track each other's progress. For instance, users may exchange step counts or calorie totals, find the process more engaging, and sustain their efforts over time. These outcomes align with social support theory, which posits that group or interpersonal dynamics are vital for maintaining motivation and perseverance. In other words, wearables' effectiveness is amplified by a robust social network—evidenced by popular app features like "team challenges" or "leaderboards." From a symbolic interactionist view, group recognition fosters higher self-identification and a stronger sense of belonging.

Social Assurance concerns an individual's belief that they will receive support and validation from others when needed. High levels of social assurance enable individuals to seek advice or moral support when wearable data reveals a shortfall (e.g., not meeting step goals), rather than giving up. Table 3 demonstrates that among those with high social assurance, the difference in health behavior outcomes between wearable users and non-users is even more pronounced. Together, these results confirm that social interaction significantly moderates the efficacy of wearable devices. Wearables alone do not guarantee better health behaviors. Instead, they work in concert with interpersonal support, which increases a user's willingness and success in forming healthy habits. For practical implementation, this means that if wearable technology can be integrated more seamlessly with social or community-based features (for instance, through well-designed mobile apps), its positive impact on health behavior can be substantially magnified.

Psychological Factors as a Moderator of the Effects of Smart Wearable Devices on Health Behavior (H3)

As shown in Tables 5 and 6, both "Personal Competence" and "Acceptance of Self and Life" significantly influence how wearable devices affect health behaviors. In short, individuals who score high on these psychological dimensions are more likely to exhibit stronger health behaviors when using wearable devices. Personal Competence here encompasses self-efficacy, self-confidence, and independent decision-making. Users with high competence can better interpret and apply the wealth of data provided by wearables, rather than being discouraged by complex metrics or perceived pressures. Individuals with greater self-efficacy persist in the face of challenges and employ strategies to overcome obstacles. They may, for example, look not only at step counts but also analyze heart rate patterns or sleep stages, engaging in more comprehensive health management.

A person's psychological state affects how they respond to feedback and resistance. The findings clearly illustrate that those who are more optimistic, confident, or accepting of themselves can transform wearable data into actionable motivation. Conversely, those with lower self-acceptance or who are quick to give up may find raw data discouraging, perceiving it as negative or intrusive instead of helpful. Bringing the three dimensions together, it's evident that health behaviors arise from a "technology × social × psychological" interaction. Wearables provide real-time, objective data that prompts immediate behavior adjustments; social networks supply interpersonal encouragement; and psychological traits determine whether users engage with or withdraw from the device's feedback. Through ANOVA, the current study confirms these significant main and interaction effects, aligning with multi-level models in behavior science that highlight the importance of multiple layers of influence.

Overall, regardless of wearable use, interpersonal support and personal psychological resilience can bolster—or constrain—healthy behaviors. However, when a person has access to a wearable device and also possesses robust social backing and positive psychological traits, the likelihood of adopting enduring health habits is noticeably higher. These insights are especially pertinent for practical applications—such as hospital programs, fitness centers, or corporate wellness initiatives—where a combined focus on technology, social facilitation, and mental well-being can optimize outcomes.

Conclusion

This study aimed to examine the impact of smart wearable devices on health behavior and to determine whether social interaction and psychological factors serve as moderators of this relationship. The findings indicate three key points: Smart wearable devices significantly enhance individuals' health behaviors (supporting H1). Social interaction (encompassing social connectedness and social assurance) moderates the relationship between wearable devices and health behavior, intensifying differences between users and non-users (supporting H2). Psychological factors, namely personal competence and acceptance of self and life, also significantly moderate this relationship (supporting H3). Below, we offer a more comprehensive synthesis, linking these results to the research questions and drawing final conclusions.

Main Effect of Smart Wearable Devices

One core issue was the relationship between smart wearable devices and health behavior. Based on ANOVA, device users scored significantly higher on the health behavior scale than non-users, and the Scheffé post-hoc test confirmed that "Device Users > Non-users." This suggests that wearable technologies (e.g., smartwatches and fitness bands) enable more precise monitoring and adjustment of daily activities, ultimately leading to healthier habits. For instance, individuals who notice they have taken too few steps may walk or jog after work, and those who see poor sleep data may improve their bedtime routine. Such real-time feedback is far more actionable than subjective self-assessments or verbal advice alone.

This finding is consistent with previous research indicating that the transparent, visual data and goal-setting features of wearables provide crucial self-monitoring and action planning support during behavior change. Wearers no longer rely solely on guesswork but instead make data-driven decisions that gradually replace poor habits with consistent health behaviors. From a public health perspective, these results underscore wearables' value as a supportive tool for individual health management.

However, because this study primarily used a cross-sectional questionnaire and specific observational periods, it cannot entirely rule out self-selection bias (e.g., people with higher health awareness may be more inclined to purchase and use wearable devices). Future investigations requiring stronger causal inferences may benefit from longer-term or experimental designs. Nevertheless, the current findings provide tangible evidence that wearables can facilitate improved health behaviors.

Moderating Role of Social Interaction

The results also highlight the significant moderating role of social interaction (including social connectedness and social assurance) on the link between wearable devices and health behavior. Specifically, people with higher-quality social interaction derive even greater benefits from wearables. In contemporary society, this is not surprising; group support and interpersonal feedback can boost both confidence and motivation, for example:

Social Connectedness: When individuals feel close to friends, family, or community, they are less likely to struggle alone in maintaining exercise routines. Wearable device data can be shared for step-count competitions, group challenges, or mutual encouragement, fostering a positive cycle of activity and social support. Social Assurance: When individuals trust that they will receive help or validation from others, they are more inclined to seek advice rather than give up if their device reports unsatisfactory results. Those with low assurance may fear criticism or simply withdraw when facing setbacks. These findings align with social support theory and symbolic interactionism, both of which underscore the importance of interpersonal engagement in sustaining behavior change. If smart wearable devices aim to maximize their impact on health behaviors, they must integrate strong social features (e.g., app-based leaderboards, group interactions, or social media sharing), promoting communal motivation rather than relying solely on individual effort.

Moderating Role of Psychological Factors

With regard to the psychological dimension, this study focused on personal competence and acceptance of self and life. Both sub-dimensions showed significant moderating effects: individuals high in personal competence or acceptance of self and life exhibited more pronounced health behavior improvements when using wearable devices. From a cognitive-behavioral or health-psychology standpoint, these two factors can be broadly explained as follows: Personal Competence: This concept encompasses self-efficacy, confidence, and problem-solving ability. When faced with a large volume of device-generated data, individuals with higher competence can interpret and use these insights to adjust their actions. Those lacking this competence may feel overwhelmed by new information or discouraged by gaps in performance, leading them to abandon the device.

Acceptance of Self and Life: This reflects an individual's positive regard for personal traits, past experiences, and current circumstances. Overly critical or self-denying individuals may become disheartened upon seeing poor performance data, whereas a more accepting mindset can transform temporary setbacks into learning opportunities, ultimately helping sustain healthy behaviors. These results indirectly support motivation theory and positive psychology. Technology itself is only a tool; genuine behavior change requires internal psychological resources. Individuals with high self-efficacy and greater self-acceptance can convert wearable-generated feedback into meaningful action rather than experiencing it as a negative stimulus.

Addressing the Overall Research Questions

Taken together, these three findings answer the study's primary hypotheses:

H1: Smart wearable devices have a positive effect on health behavior—confirmed by empirical analysis.

H2: Social interaction serves as a moderator—higher levels of social connectedness and social assurance amplify the benefits of wearables.

H3: Psychological factors also serve as a moderator—people with stronger personal competence and higher self-acceptance demonstrate greater health behavior improvements with wearable use.

Hence, while wearable devices can facilitate healthier behaviors, their effectiveness is not absolute but rather contingent on social and psychological contexts. From a behavioral science perspective, this underscores the multi-layered nature of behavior change. From a practical standpoint, without incorporating interpersonal support and psychological motivation, technology alone may have limited results. Overall, these conclusions validate the efficacy of wearable devices in boosting health behaviors while emphasizing the decisive influence of social interaction and psychological factors. Not only do these insights deepen theoretical understandings of health behavior, but they also provide strategic guidance for policymakers and practitioners looking to promote wearable technology effectively.

Future Developments and Research Directions

Continued Technological Innovation

Wearable devices may integrate additional sensing technologies (e.g., blood oxygen levels, stress hormone monitoring) and AI coaching capabilities, refining the quality of professional feedback and bolstering social interaction features.

Interdisciplinary Collaboration

Because improving health behavior is inherently multifaceted, future initiatives or research should unite experts in public health, psychology, and information engineering. Such cross-sector teamwork could build comprehensive, personalized health management programs.

Adaptation for Diverse Populations

Different demographic groups—such as older adults, children, and individuals with chronic health conditions—might need tailored scales and device usage protocols. Seniors, in particular, may struggle with interface design or digital literacy, requiring more intuitive or simplified options. Smart wearable devices have brought significant opportunities to the health-promotion field. Their actual impact, however, depends not only on device functionality but also on the user's social interaction and psychological state. This study, guided by three hypotheses (H1, H2, H3), confirms that wearable use, social factors, and individual psychological traits are deeply intertwined in shaping health behaviors. Consequently, government agencies and corporations intending to promote such devices must go beyond technical efficiency and ease of use, paying close attention to users' levels of social support, self-efficacy, and acceptance. Only by uniting technology, social networks, and psychological elements can we create a sustainable ecosystem for positive, long-term behavior change.

Overall, quantitative data here verifies that wearable devices can significantly enhance users' health behaviors, with social interaction and psychological factors serving as moderating influences. This conclusion not only advances academic theory but also informs practical applications. Future endeavors in public health campaigns, corporate wellness initiatives, and personal improvement can leverage these insights to plan and optimize strategies for a healthier lifestyle.

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