

The roles, functions, and types of quantified health-related feedback information on smart device

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Abstract:

This research examines the mechanisms by which Quantified Self (QS) information and feedback modalities delivered via wearable smart devices support individuals' pursuit of health-related goals. Although smart bands and smartwatches continuously generate quantified physical activity and health data, prior research has focused largely on raw numerical outputs, leaving unclear which informational functions strengthen motivation and how transformed feedback modalities shape actual behavior. Across two studies, we investigated how specific informational functions shape motivation to pursue goals (Study 1) and how the interaction between social comparison feedback and goal-framing feedback influences actual goal-directed behavior (Study 2). In Study 1, we analyzed survey data from 321 smart-band users using structural equation modeling. The results showed that all three primary informational functions — information about physical activity, health status, and rewards — significantly and positively increased goal-pursuit motivation, with physical activity information emerging as the strongest predictor ($\beta = .445, p < .001$). In Study 2, a 2 (social comparison: downward vs. upward) $\times$ 2 (goal-frame: to-date vs. to-go) between-subjects experiment ($N = 109$) was conducted using an actual walking task. The two-way ANOVA revealed a statistically significant interaction effect on the proportion of post-feedback steps. Specifically, downward comparison feedback paired with a to-go frame elicited significantly higher goal-directed behavior than when paired with a to-date frame, whereas upward comparison feedback combined with a to-date frame was significantly more effective than when combined with a to-go frame. These findings demonstrate that tailoring goal framing to the specific motivational state induced by social comparison optimizes behavioral adherence. Practically, the results indicate that developers of smart bands and mobile healthcare applications should match the framing of progress information to the direction of social comparison feedback, offering critical theoretical and practical implications for user interface and gamification design in mobile digital healthcare.

Key Words: Wearable activity trackers; Self-tracking behavior; Social comparison; Goal framing (to-date vs. to-go); Goal-pursuit motivation; Gamified health applications

Introduction

Digital healthcare is primarily implemented through wearable devices, such as smartwatches and smart bands. Specifically, these wearable devices are attached to the user's body to measure and store physiological changes resulting from physical activities in real time, thereby providing quantified data to the users. In academic literature, this data-driven self-tracking phenomenon is conceptualized under the term Quantified Self (QS) (Swan, 2013). QS refers to the practice of individuals voluntarily managing their daily health through quantitative metrics — such as physical activity volume, calorie expenditure, heart rate, and oxygen saturation — monitored via wearable devices or smartphone applications (Karapanos, Gouveia, Hassenzahl, & Forlizzi, 2016; Pettinico & Milne, 2017). Ultimately, such numerically represented data are provided to help users better understand their physical activities and to motivate behavioral changes toward a healthier lifestyle (Lee & Sung, 2018; Patel, Asch, & Volpp, 2015).

The quantified information provided by wearable devices, such as smartwatches and fitness trackers, can be broadly categorized into three distinct functions. First, they measure physical activity levels, including step counts, calorie expenditure, travel distance, and active minutes. Second, these devices monitor health status indicators, such as heart rate, blood oxygen saturation, blood pressure, respiration rate, and electrocardiogram (ECG). Lastly, contemporary smart devices synchronize these generated physical and health metrics with mobile healthcare applications to transform and present data in diverse modalities. This transformed information incorporates gamification elements into exercise, thereby fostering user engagement and interest in physical activity (Yang, Hu, & Koenigstorfer, 2022). For instance, based on step count data measured by a smartwatch (e.g., achieving a daily step goal), the healthcare application provides various continuous rewards, such as virtual trophies or badges. These gamified rewards enhance user interest in exercise and physical exertion; thus,

quantified data from smart devices can effectively deliver reward mechanisms through integrated healthcare applications.

According to goal setting theory, the provision of physical and health-related quantitative information has been shown to enhance the goal pursuit motivation of smartwatch users (Hermsen, Frost, Renes, & Kerkhof, 2016; Sullivan & Lachman, 2017). Empirically, Siepmann and Kowalczyk (2021) demonstrated that the quantified data provided by smartwatches exert a positive influence on users' goal pursuit motivation. However, their study is limited in that it failed to examine the reward functions inherent in quantified information. In this regard, Song and Yao (2022) posited that the reward functions of smartwatches allow users to experience a sense of goal achievement, and Suh, Wagner, and Liu (2018) argued that digital badges as a reward mechanism signify accomplishment and status, thereby inducing user effort toward goal attainment. Consequently, there is a need to empirically analyze the effects of the three distinct information functions of quantified smart devices — namely, physical activity information, health status information, and reward functions — on users' goal pursuit motivation. Based on the prior studies, this research first attempted to test the following hypothesis.

Hypothesis 1: The three informational functions provided by smart devices (physical activity information, health status information, and rewards) positively affect goal pursuit motivation.

Drawing upon the goal-setting theory formulated by Latham and Locke (1991), Karapanos et al. (2016) and Pettinico and Milne (2017) investigated the feedback effects inherent in the Quantified Self (QS) phenomenon. Their findings demonstrate that when QS functions as constructive feedback that facilitates the attainment of healthcare goals, it exerts a positive influence on enhancing an individual's goal-directed behavior.

QS-based quantified data regarding physical and health-related metrics are converted into various modalities of feedback and delivered to users. That is, while smart devices can directly present QS data to users, they are more commonly integrated with smartphone applications to transmute QS metrics into diverse forms of visual feedback. For instance, if a user walks 9,200 steps in a single day, the smart band displays the QS data merely as the numeral 9,200. However, the synchronized application can present this QS data in highly varied and modified formats—either by benchmarking against peers (e.g., Your total step count today places you ahead of or behind 70% of other users) or by indicating the degree of target achievement relative to personal goals (e.g., You are 800 steps away from your target goal of 10,000 steps). Despite the potential to transform and deliver quantified health and physical activity QS metrics in such multi-faceted formats, prior studies (Karapanos et al., 2016; Pettinico & Milne, 2017) are limited by their primary focus on the raw numerical data displayed on smart devices. Consequently, there is a compelling need to investigate how transforming device-generated QS data into diverse feedback modalities influences users' goal-directed behaviors, such as walking patterns and overall physical exercise volume.

Review of Literature

Quantified self (QS)-based feedback modalities and goal-directed behavior

Pettinico and Milne (2017) demonstrated that users with health-related goals exhibit an increased intention to engage in goal-directed behaviors when they perceive Quantified Self (QS)-based information as useful feedback. This prompts the question: under what conditions and through what mechanisms do users perceive QS data as valuable feedback? Prior research suggests that such perception is facilitated when internal motivation for the target behavior is heightened (Lee & Sung, 2018). Internal motivation is broadly categorized into two distinct dimensions: self-enhancement and self-improvement. While the self-enhancement motive represents the desire to maintain and reinforce a positive self-concept, the self-improvement motive entails the desire to challenge one's current self-view and enhance competencies by seeking better pathways toward goal achievement.

Among the various modalities of QS-based feedback, Lee and Sung (2018) identified social comparison feedback and goal-frame feedback as two prominent types that exert highly significant influences on goal-directed behavior. Consequently, it is imperative to investigate which specific type of internal motivation (self-enhancement versus self-improvement) is activated by these two feedback modalities to subsequently promote goal-directed behavior.

Social comparison feedback. Social comparison feedback can be divided into two types based on the direction of comparison. First, *downward comparison* involves comparing oneself with others who possess inferior attributes. This function satisfies the self-enhancement motive and bolsters self-efficacy, thereby mitigating anxieties associated with potential goal failure (Cha & Lee, 2015; Tormala & Petty, 2004). Concurrently, however, because the characteristics of the comparison target reduce opportunities to acquire information necessary for self-growth and skill enhancement, individuals may infer that they could eventually regress to the level of their inferior counterparts; this, in turn, serves to stimulate the self-improvement motive over time (Buunk & Ybema, 1997; Han, 1999). In contrast, *upward comparison* entails evaluating oneself against superior peers. Through upward comparison, individuals acquire competence-enhancing information regarding areas requiring further development based on the superior attributes of others, thereby satisfying their self-improvement motive (Han, 1999). Nevertheless, because this comparison inevitably threatens self-esteem

and induces negative affect due to the superior status of the target, it consequently drives an increase in the self-enhancement motive to counteract these negative emotions (Brickman & Bulman, 1977).

For instance, mobile health applications allow users to evaluate their daily step counts relative to others. Suppose a user reviews their total daily steps around 7:00 PM after dinner and learns that their performance places them ahead of 70% of other users (downward comparison). This realization—that they walk more than the average population—will likely foster positive expectations and confidence regarding their physical health (satisfying the self-enhancement motive). However, since five hours remain until midnight, the awareness that complacency might cause them to fall back toward the average step count may motivate them to walk further (increasing the self-improvement motive). Conversely, under identical circumstances, if the user discovers that they lag behind 70% of other users (upward comparison), this provides a concrete impetus to contemplate areas needing improvement. If they walk sufficiently during the remaining time, they can surpass the average step count (satisfying the self-improvement motive). Yet, this situation simultaneously triggers negative affect from lagging behind and induces anxiety about whether they can realistically exceed the average within the remaining hours. To cope with this, the user may engage in self-reassurance (e.g., I can certainly do this), thereby heightening the self-enhancement motive. Thus, it can be inferred that different internal motivational factors are activated depending on the specific type of social comparison feedback. Empirically supporting this mechanism, Han (1999) and Lee and Sung (2018) demonstrated that downward comparison feedback enhances the self-improvement motive, whereas upward comparison feedback amplifies the self-enhancement motive, both ultimately enabling the sustained pursuit of goal-directed behaviors.

Goal-frame feedback. Goal-frame feedback is likewise classified into two distinct types. First, the *to-date frame* emphasizes actions completed thus far. By highlighting the level of achievement attained up to the present moment, this frame prompts individuals to infer their level of commitment toward the goal. In contrast, the *to-go frame* presents the remaining or missing goal behaviors necessary for goal completion. By emphasizing the discrepancy between the current state and the goal achievement, this frame encourages individuals to estimate the amount of effort required to successfully attain the goal in the future (Kim, Kang, & Kwon, 2014; Koo & Fishbach, 2008). For example, a user can monitor how much of his daily 2,000 kcal expenditure goal has been met (e.g., 1,000 kcal consumed to date) via a smartphone application synchronized with his smart band. This type of feedback directs attention to current achievements, influencing him to perceive the goal as important and valuable to the extent that he feels committed to it (Koo & Fishbach, 2008). Alternatively, in the exact same scenario, he could be presented with information indicating how much energy expenditure remains to reach his daily target (e.g., 1,000 kcal remaining to reach the goal). In this case, the feedback highlights the magnitude of the discrepancy between the final goal and his current state, prompting him to seek active strategies to reduce this gap (Fishbach, Koo, & Finkelstein, 2014; Kim et al., 2014).

Interaction between social comparison and goal-frame feedback. Lee and Sung (2018) posited that different types of social comparison feedback may necessitate corresponding types of goal-frame feedback. Specifically, it was argued that the to-date frame emphasizes completed actions as achievement-oriented feedback, which allows individuals to infer their commitment to the goal; consequently, it can increase goal-directed behavior by enhancing the self-enhancement motivation activated by upward comparison. On the other hand, because the to-go frame emphasizes the discrepancy between the current status and goal attainment—thereby drawing focus to the process of goal achievement—it can reinforce the self-improvement motive activated by downward comparison, subsequently driving goal-directed behavior. Accordingly, this study attempted to investigate the interactive effects of QS-based social comparison feedback (downward vs. upward comparison) and goal-frame feedback (to-date vs. to-go frame) on users' goal-directed behaviors. The followings are specific hypotheses provided by the review of literature.

Hypothesis 2: Under the downward comparison condition, individuals provided with a to-go frame will exhibit a higher level of goal-directed behavior than those provided with a to-date frame.

Hypothesis 3: Under the upward comparison condition, individuals provided with a to-date frame will exhibit a higher level of goal-directed behavior than those provided with a to-go frame.

Materials and methods

The present research was conducted across two distinct studies. Specifically, Study 1 empirically analyzed the effects of three informational functions of smart devices—namely, physical activity information, health status information, and rewards—on goal pursuit motivation. Subsequently, Study 2 investigated the interactive effects of QS-based social comparison feedback (downward vs. upward comparisons) and goal-frame feedback (to-date vs. to-go frame) on individuals' goal-directed behaviors.

Study 1

Participants and sampling. The participants for Study 1 consisted of 334 adult male and female residing in J City at South Korea, who actively use smart bands. For the sampling method, a survey was conducted utilizing convenience sampling. Out of a total of 334 respondents, questionnaires completed by 321 participants were used for the final analysis, excluding 13 who provided insincere responses. Regarding the gender distribution of the participants, 182 were male (56.7%) and 139 were female (43.3%). Data were collected from

members of a comprehensive sports complex located within a national university in J City who routinely wear smart bands. Notably, this sports complex, which opened in June 2021, features fully digitalized fitness center equipment. Members can easily monitor their exercise logs and physical activity metrics via smart bands provided to them by the center free of charge.

Measures and data analysis. This study employed a questionnaire to analyze the effects of the three informational functions of smart bands (physical activity information, health status information, and rewards) on goal pursuit motivation. The measurement scales adopted from prior research were modified and adapted to fit the specific context of this study, with all items evaluated on a 7-point Likert scale (*very disagree: 1 – very agree: 7*). Specifically, the physical activity information function was assessed using five items adapted from the self-quantification scale developed by Maltseva and Lutz (2018) and the information feedback scale proposed by Hsu and Lu (2007). The health status information function comprised three items modified from the informativeness scale employed by Hausman and Siekpe (2009). For the rewarding function, four items were adapted from the metrics utilized by Suh et al. (2018). Lastly, goal-pursuit motivation was evaluated using six items modified from the scale developed by Zhang et al. (2019), with all aforementioned items adapted to fit the specific purpose of the present study. To analyze the data collected in Study 1, statistical analyses were performed using IBM SPSS version 26.0 and AMOS version 26.0.

Study 2

Participants and experimental design. Similar to Study 1, the participants for Study 2 consisted of 120 members of a comprehensive sports complex located within a national university in J City at South Korea who routinely wear smart bands. Of the 120 participants, 11 who failed the feedback manipulation check were excluded from the analysis. The final sample of 109 participants consisted of 67 males (61.5%) and 42 females (38.5%), with a mean age of 41.4 years ($SD = 7.80$, range = 20–54). Each participant was informed that they were participating in the study alongside 109 fellow members. Study 2 employed an experimental design based on a 2 (social comparison feedback: upward vs. downward comparison) x 2 (goal-frame feedback: to-date vs. to-go frame) between-subjects factorial design.

Experimental procedure. The experiment was conducted over a two-day period, starting at 12:00 PM on Day 1 and concluding at 12:00 PM on Day 2. Upon arriving at the sports complex fitness center on the first day, participants were read a newspaper article regarding the positive effects of regularly walking more than 10,000 steps a day on physical health. Following this, they were assigned a health-management goal to walk as much as possible throughout the day. After receiving general instructions for the experiment, participants wore the smart bands and left the fitness center to begin their daily activities from 12:00 PM on Day 1 until 12:00 PM on Day 2. During the activity period, under the guidance of research assistants, participants transmitted their QS data (i.e., accumulated step count to that point) displayed on their smart bands to the smartphones of four research assistants at two specific time points: 6:00 PM and just before 12:00 AM. Based on the cumulative step count recorded up to 6:00 PM, the research assistants immediately transmitted one of four pre-designed feedback stimuli to each participant's smartphone. These stimuli were manipulated according to the independent variables: social comparison (downward vs. upward comparisons) and goal-frame (to-date vs. to-go frame).

The QS feedback types were designed to closely mimic interfaces commonly provided by commercial health applications synchronized with smartwatches or smart bands (see Figure 1). First, the social comparison QS metric was positioned at the top-center of the feedback image. In the downward comparison condition, it was presented as a message stating, *As of [Month/Day] at the current time (6:00 PM), you are ahead of 70% of other users*. Conversely, in the upward comparison condition, the message was stated, *As of [Month/Day] at the current time (6:00 PM), you are lagging behind 70% of other users*. The goal-frame QS feedback visually diagrammed the cumulative step count achieved up to 6:00 PM using a horizontal linear progress bar in the center of the feedback image. Specifically, the to-date frame intuitively illustrates the goal-pursuit process by labeling 0 steps at the left end and 10,000 steps at the right end of the line, with a thick line highlighting the interval from 0 steps to the currently accumulated steps. In contrast, the to-go frame featured a thick line highlighting the remaining interval from the currently accumulated steps to 10,000 steps.

Furthermore, depending on the framing condition, explanatory text was provided beneath the progress bar: *You have walked 0,000 steps toward your 10,000-step goal* for the to-date frame, and *You have 0,000 steps remaining to reach your 10,000-step goal* for the to-go frame. Therefore, this study employed the four types of experimental stimuli:

- (1) downward comparison/to-date frame,
 - (2) downward comparison/to-go frame,
 - (3) upward comparison/to-date frame, and
 - (4) upward comparison/to-go frame.
- To control for exogenous variables that might affect the experimental results, participants were allocated to one of the four stimulus conditions via random assignment. The outcome variable, goal-directed behavior, was operationalized and measured as the net step count accumulated after the delivery of feedback, specifically from 6:00 PM until just before 12:00 AM. On Day 2, participants came back to the fitness center by 12:00 PM to return their smart bands.

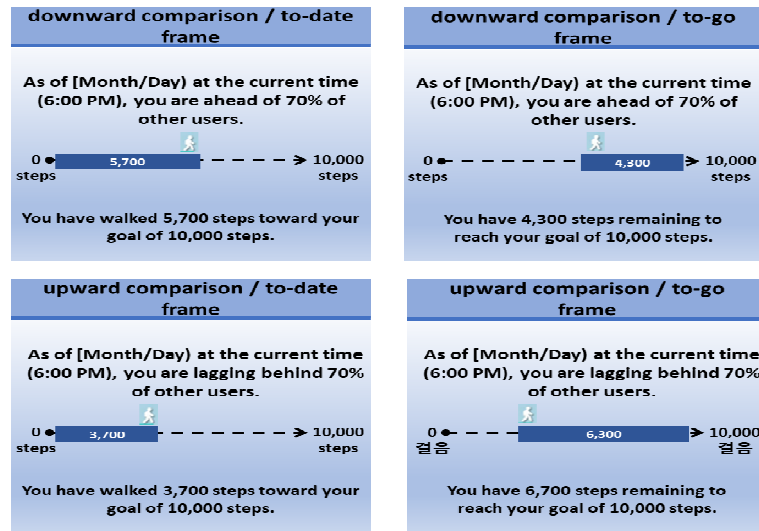


Figure 1. Four types of experimental stimuli

Manipulation checks and measures. Manipulation checks for both social comparison and goal-frame feedback were conducted via a post-experimental questionnaire. Participants were presented with a template of the feedback image, wherein the locations of the social comparison and goal-frame metrics were highlighted with red boxes and labeled as [A] and [B], respectively. To assess the social comparison manipulation, participants were asked to fill in the blank for the following statement: *Label [A] indicates that, compared to other participants in this program, I am currently () by 70%.* They must choose between two options: (1) ahead or (2) lagging behind. The manipulation was deemed successful if participants in the downward comparison condition select option (1) and those in the upward comparison condition select option (2).

For the goal-frame manipulation check, the following statement was provided: *Based on a 10,000-step target, label [B] emphasizes the information regarding ().* Participants selected either (1) the number of steps accumulated thus far or (2) the number of steps remaining to be walked. The manipulation was considered successful if participants in the to-date frame condition selected option (1) and those in the to-go frame condition select option (2). Participants who failed either of these manipulation checks were excluded from subsequent data analyses. For reference, among the 120 participants, a total of 7 participants failed the manipulation checks for the social comparison and goal framing feedback.

The dependent variable—goal-directed behavior—was operationalized as the proportion of steps accumulated after the delivery of feedback relative to the total daily step count. The post-feedback step count was calculated by subtracting the steps recorded up to 6:00 PM on Day 1 from the total step count. For instance, if a participant reports 3,500 steps at 6:00 PM and 10,000 steps just before midnight to the research assistant, their total step count is 10,000, and their post-feedback step count is 6,500. Goal-directed behavior is formally measured using the following formula: $\text{post-feedback step count} / \text{total step count} \times 100$.

This represents the proportion of post-feedback step counts relative to the total daily step count. For instance, if a participant accumulated 6,500 steps after receiving feedback (a total daily step count = 10,000, 65% of the total step count was recorded as post-feedback accumulation for the analysis). The primary rationale for employing this proportional metric rather than absolute counts was to control for baseline individual variances in participants' daily walking habits. For Study 2, the average percentage of steps taken after the feedback relative to the total steps was 59.36% (Min. = 3.38%, Max. = 93.36%, SD = 18.23%).

Data analysis. Statistical analyses for Study 2 were performed using IBM SPSS version 26.0. Specifically, to examine variations in goal-directed behavior across the different Quantified Self (QS) feedback conditions, a 2 (social comparison: downward vs. upward comparison) $\times$ 2 (goal-frame: to-date vs. to-go frame) analysis of variance (ANOVA) was conducted.

Results

Study 1

Reliability and validity. To evaluate the reliability of the measurement items for Study 1, Cronbach's α coefficients were calculated to assess internal consistency, using a benchmark criterion of $\alpha > .70$. The reliability analysis revealed that the Cronbach's α values for all variables exceeded .70, as detailed in Table 2, confirming that the measurement instruments employed in this study possess high internal consistency. To validate the construct validity of the measurement scales, a confirmatory factor analysis (CFA) was performed using AMOS 26.0. The analysis demonstrated an acceptable model fit: $\chi^2=362.828$, $df=132$ ($p<.001$), TLI=.946, CFI=.952, RMSEA=.066, SRMR=.0432. Furthermore, all factor loadings for the measurement items ranged from .623 to .937, indicating statistical significance; the detailed factor loadings are presented in Table 2. The composite

reliability (CR) values ranged from .819 to .911, all of which surpassed the recommended threshold of .70, thereby verifying the reliability of the measurement scales (Hair et al., 1988).

The Average Variance Extracted (AVE) values ranged from .549 to .675. In general, convergent validity is established when the AVE values exceed .50 (Fornell & Larcker, 1981), whereas discriminant validity is supported when the AVE of each construct is greater than the squared correlation coefficients between that construct and any other constructs. As shown in Table 1 and Table 2, the AVE values for all variables were greater than .50 confirming the convergent validity of the variables, while the AVE values for all variables were higher than the corresponding squared correlation coefficients confirming the discriminant validity of the variables.

Table 1. Results of the correlations among variables

	M	SD	1	2	3	4
1. PAI	5.28	.95	1			
2. HSI	5.34	.92	.74(.54)	1		
3. RE	4.58	1.12	.52(.27)	.43(.18)	1	
4. GPM	5.31	1.13	.63(.39)	.60(.36)	.59(.34)	1

Note: PAI=Physical Active Information function, HSI=Health Status Information function, RE=Rewarding function, GPM=Goal-

Pursuit Motivation. Values in parentheses represent the squared correlation coefficients between variables.

Table 2. Results of the confirmatory factor analysis

Factors	Items	Factor Loadings	C. R.	AVE	α
PAI	PAT 1	.823	.881	.675	.904
	PAT 2	.832			
	PAT 3	.861			
	PAT 4	.852			
	PAT 5	.623			
HSI	HSM 1	.824	.851	.675	.872
	HSM 2	.816			
	HSM 3	.799			
RE	RE 1	.768	.819	.549	.836
	RE 2	.821			
	RE 3	.909			
	RE 4	.937			
GPM	GPM 1	.871	.911	.608	.931
	GPM 2	.864			
	GPM 3	.805			
	GPM 4	.869			
	GPM 5	.871			
	GPM 6	.856			

Results of hypothesis 1. Prior to testing Hypothesis 1, the goodness-of-fit of the structural model was evaluated. The structural model fit indices were as follows: $\chi^2=376.814$, $df=132(p<.001)$, TLI=.942, CFI=.949, RMSEA=.069, SRMR=.0462.

Considering these fit indices collectively, the proposed structural model was deemed acceptable and appropriate for further analysis (Hu & Bentler, 1999). Subsequently, the standardized path coefficients and their statistical significance within the structural equation model were examined to test the hypotheses.

The comprehensive estimation results were summarized in Table 3. In terms of the specific relationships among the variables, the findings are as follows. First, the standardized path coefficient from the physical activity information to goal-pursuit motivation was found to be statistically significant and positive ($\beta = .445$, $p < .001$), indicating that the physical activity information function of smart bands significantly enhances goal-pursuit motivation.

Second, the health information function also exerted a significant positive effect on goal-pursuit motivation, with a standardized path coefficient of $\beta = .312(p < .001)$. Lastly, the rewarding function of smart bands displayed a significant positive influence on goal-pursuit motivation ($\beta = .299$, $p < .001$). Consequently, Hypothesis 1 was fully supported.

Table 3. Results of structural equation modelling ($N = 321$)

Hypothesis 1	B	β	SE
PAI $\rightarrow$ GPM	.496	.445***	.092
HSI $\rightarrow$ GPM	.245	.312***	.101
RE $\rightarrow$ GPM	.226	.299***	.056

Note: PAI=Physical Active Information function, HSI: Health Status Information function, RE: Rewarding function, GPM: Goal-Pursuit Motivation. ***: $p < .001$

Study 2

Manipulation checks. As mentioned previously, for the social comparison manipulation check, participants were asked to fill in the blank for the following statement: *Label [A] indicates that, compared to other participants in this program, I am currently () by 70%.* They must choose between two options: (1) ahead or (2) lagging behind. The manipulation was deemed successful if participants in the downward comparison condition select option (1) and those in the upward comparison condition select option (2). Among the 60 participants assigned to the downward comparison condition, four incorrectly selected option (2). Similarly, of the 60 participants in the upward comparison condition, three incorrectly selected option (1). Consequently, these seven participants were excluded from subsequent data analyses.

For the goal-frame manipulation check, participants were asked to fill in the blank for the following statement: "Based on a 10,000-step target, label [B] emphasizes the information regarding ()." Participants selected either (1) the number of steps accumulated thus far or (2) the number of steps remaining to be walked. The manipulation was considered successful if participants in the to-date frame condition selected option (1) and those in the to-go frame condition select option (2). Among the 60 participants assigned to the to-date frame condition, two incorrectly selected option (2). Similarly, of the 60 participants in the to-go frame condition, two incorrectly selected option (1). Consequently, these four participants were excluded from subsequent data analyses.

Results of hypotheses 2-3. To analyze the differences in the level of the goal-directed behavior across feedback conditions, a 2 (social comparison: downward vs. upward) $\times$ 2 (goal-frame: to-date vs. to-go) ANOVA was conducted. As mentioned previously, the dependent variable was the proportion of post-feedback steps relative to the total step count. Results of ANOVA revealed a statistically significant interaction effect between social comparison and goal frame on the level of the goal-directed behavior ($F = 6.96, p < .01$). Detailed results are presented in Table 4 and Figure 2.

To test the specific hypotheses, planned contrasts were performed. The results indicated that during one day of wearing and living with a smart band, the downward $\times$ to-go frame condition ($M = 65.69, SD = 17.23$) yielded a significantly higher proportion of post-feedback steps than the downward $\times$ to-date frame condition ($M = 44.85, SD = 15.28; F = 4.791, p < .05$). Conversely, the upward $\times$ to-date frame condition ($M = 62.35, SD = 15.29$) showed a significantly higher proportion of post-feedback steps than the upward $\times$ to-go frame condition ($M = 46.37, SD = 16.36; F = 4.212, p < .05$). In other words, downward comparison combined with a to-go frame, and upward comparison combined with a to-date frame, were more effective in promoting goal-directed behavior when provided as feedback. Consequently, both Hypothesis 2 and Hypothesis 3 were supported.

Table 4. Results of ANOVA ($N = 109$)

Sources	SS	DF	MS	F
Social Comparison (A)	73.12	1	73.12	18.48***
Goal Frame (B)	33.06	1	33.06	9.25***
A X B	42.29	1	42.29	6.96**

Note: *** $p < .001$, ** $p < .01$

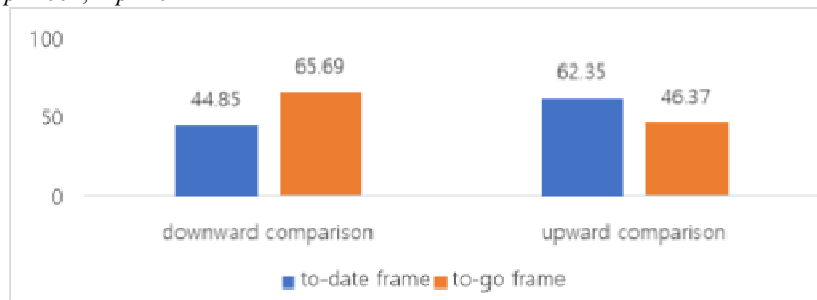


Figure 2. Mean step counts by social comparison and goal frame

Discussion

The present research was conducted across two distinct studies. Specifically, Study 1 attempted to examine the effects of three informational functions of smart devices—namely, physical activity information, health status information, and rewards—on goal pursuit motivation. Subsequently, Study 2 aimed to investigate the interactive effects of QS-based social comparison feedback (downward vs. upward comparison) and goal-frame feedback (to-date vs. to-go frame) on individuals' goal-directed behaviors. The discussion based on the research findings is as follows.

The empirical results of Study 1 provide meaningful insights into how specific functions of smart bands influence users' goal-pursuit motivation, fully supporting Hypothesis 1. These results are partially consistent with a prior study (Kang, Yang, & Lim, 2024). Most notably, the physical activity information function emerged as the most powerful predictor of goal-pursuit motivation. This finding suggests that real-time feedback on physical metrics (e.g., step counts, distance, calories burned) plays a paramount role in driving user behavior. From a psychological standpoint, such immediate informational feedback enhances users' perceived competence (Ryan & Deci, 2000) and self-efficacy (Bandura, 1997), which in turn strengthens their commitment to health-related goals. This aligns with prior research on wearable technology, which posits that self-monitoring features are critical catalysts for continuous behavioral change (Sullivan & Lachman, 2017) and goal-pursuit motivation (Zhang et al., 2019). Furthermore, both the health information function and the rewarding function significantly boosted goal-pursuit motivation. The positive impact of health information implies that users value holistic health insights (e.g., sleep quality and heart rate) to manage their long-term well-being. Concurrently, the significant effect of the rewarding function confirms the utility of gamification elements (e.g., virtual badges, streaks, and milestone achievements) in smart bands. Interestingly, however, the relatively lower path coefficient of the rewarding function compared to other two information functions suggests that while extrinsic rewards are beneficial, internal driven feedback derived from data monitoring remains the primary driver of goal-pursuit motivation among smart band users. From a practical point of view, rather than merely designing extrinsic reward systems such as points or coupons, smart band developers and healthcare application planners should allocate more resources to enhance dashboard user experience, thereby enabling users to monitor their physical activity and health information in a more intuitive and comprehensible manner.

The empirical results of study 2 confirm that the interaction between social comparison and goal framing has a significant effect on sustaining individuals' goal-directed behavior. Specifically, individuals who received downward comparison feedback—indicating that their physical activity for health management was higher than that of other users—experienced an increase in self-improvement motivation. For this group, paired with a to-go frame that highlights the discrepancy between their current status and the final goal is more advantageous for activating intrinsic motivation toward goal-directed behavior. Conversely, those who received upward comparison feedback, showing lower physical activity than their peers, exhibited heightened self-enhancement motivation. For these individuals, presenting information that emphasizes what they have already achieved in the goal-pursuit process (to-date frame) is more effective in stimulating their intrinsic motivation. All of these findings are consistent with a previous study (Lee & Sung, 2018). These findings imply that merely developing Internet of Things (IoT) technology in a newer and more innovative manner is insufficient to enrich users' lives. From the user's perspective, the perceived utility of wearable devices is heightened primarily when the technology is effective for health management (Lee & Lee, 2020). Currently, health applications integrated with wearable devices are designed to allow users to easily compare their performance with others at the touch of a button. That is, users are exposed to either upward or downward social comparisons based on their step counts, yet their goal attainment progress is exclusively presented in a to-date frame. If the social comparison experienced during wearable device usage enhances self-efficacy and mitigates the anxiety of failing to achieve goals, it can effectively sustain goal-directed behavior. Conversely, if users experience damaged self-esteem or negative affect, it may pose an ego threat, subsequently reducing their commitment to the goal-directed behavior.

Conclusions

This research indicated that the three primary functions of smart bands—namely physical activity information, health information, and rewards—exert a positive influence on goal-pursuit motivation, which in turn fosters physical activity adherence. Thus, practitioners must continuously enhance the functional efficacy of physical activity and health information provided by smartwatches and bands, while simultaneously integrating diverse reward mechanisms to stimulate user interest in these features. Doing so will not only heighten users' goal-pursuit motivation but also ultimately augment their continuance intention toward these smart devices.

In addition, this research indicated that there were the interactive effects of QS-based social comparison feedback (downward vs. upward comparison) and goal-frame feedback (to-date vs. to-go frame) on users' goal-directed behaviors. Specifically, for users exposed to downward comparison feedback, their self-improvement motivation increases; thus, combining this with a to-go frame that underscores the remaining discrepancy to goal achievement is more conducive to fostering intrinsic motivation. In contrast, for users receiving upward comparison feedback, self-enhancement motivation becomes prominent. Thus, reinforcing their intrinsic motivation for goal-directed behavior is more effectively achieved by providing feedback on their accumulated achievements during the goal-pursuit process (to-date frame).

The two types of goal framing, the to-date and to-go frames, serve as highly valuable information for representing progress toward goal attainment, significantly influencing the intrinsic motivation activated by social comparison. Because goal framing can be presented not only textually but also schematically, an optimal combination of framing and social comparison can offer meaningful insights that assist consumers in managing their goals. Given that smart bands are predominantly utilized in tandem with smartphones, the findings of this research are expected to offer modest yet substantive contributions to guiding the strategic development of the smart healthcare industry.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Google Gemini Pro for language editing and improvement of academic English. After using this tool/service, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Conflicts of interest

No potential conflict of interest was reported by the authors.

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