

Design and evaluation of persuasive strategies for promoting physical activity in wearable systems

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Abstract

INTRODUCTION: Persuasive technology offers a technological approach to promote physical activity.

OBJECTIVES: This study aims to design and evaluate user perceptions of various persuasive strategies in a wearable system.

METHODS: Six persuasive strategies were implemented in a wearable system comprising a sensing strap, an Android application, and a data server. A pilot user study assessed perceived persuasive efficacy via post-study questionnaires and diaries.

RESULTS: The findings indicated that social influence, goal setting, and reinforcement significantly correlated with persuasive efficacy; personal awareness, enjoyment interaction, and suggestion and reminders did not. All six strategies significantly increased sustained usage intention.

CONCLUSION: A multi-strategy persuasive wearable system can enhance sustained usage intention and exercise motivation, with complementary roles of different strategies, demonstrating its potential for health behavior interventions.

Keywords: persuasive technology, wearable system, physical activity promotion, user study

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1. Introduction

A growing number of individuals worldwide lead sedentary lifestyles, contributing to a broad spectrum of health problems and chronic conditions, including obesity, heart disease, cancer, and diabetes [1]. Additionally, mental health concerns such as depression and anxiety are further aggravated by inadequate physical activity. This affects populations across most regions of the globe and is threatening the life expectancy over the past century [2]. As reported by the World Health Organization (WHO), more

than 80% of adolescents and 27% of adults are insufficiently physically active, making this one of the most urgent public health issues of the contemporary era [3].

In today's society, it can be challenging to incorporate regular exercise into our daily routines, primarily because many people rely on motorized transportation—even those who intend to change their sedentary behaviors [4]. Sustaining long-term adherence to exercise-related commitments is still a major challenge for a substantial proportion of the population. In fact, many individuals begin health-related endeavors such as joining a gym or adopting

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dietary interventions, only to abandon them prior to achieving their predetermined goals. This challenge becomes even more pronounced for those engaged in sedentary occupations, for whom consistently achieving exercise goals is particularly difficult [5].

The design of technologies targeting attitude and behavioral change is far from trivial. Research has explored technological interventions that support the initiation and maintenance of an active lifestyle, especially among exercise beginners. Persuasive technology, which aims to change attitudes or behaviors [6], has the potential to encourage increased physical activity [7]. This research aimed to develop and evaluate a customized computing system that supports individuals' desire for behavioral change, with a specific focus on promoting walking as a lifestyle change strategy. To achieve this objective, we designed a wearable exercise system that incorporates persuasive technology concepts into its functional design to promote physical activity. The system comprised three components forming an acquisition, processing, and feedback pipeline: (1) a wearable strap equipped with electrocardiogram (ECG) sensors and an accelerometer for monitoring of cardiac activity and physical movement; (2) an Android-based interactive application developed to process physiological signals in real time, extract exercise metrics, and present performance feedback; and (3) a remote server dedicated to store and manage data.

Assessing the efficacy of persuasive technologies in achieving behavioral change requires long-term, large-sample empirical studies. Furthermore, a fully functional prototype is a prerequisite for evaluating the effectiveness of the strategies designed to promote physical activity. This study reports the findings from a pilot user study, which was designed to rapidly and cost-effectively assess users' experiences with the proposed wearable exercise system. A list of persuasive strategies targeting increased physical activity was integrated into the system's functional modules, encompassing goal setting, personal awareness, social influence, reinforcement, suggestion and reminder, and enjoyable interaction. A one-week field study was conducted with 25 participants who used the system continuously. The efficacy of the persuasive strategies was evaluated based on participants' perceptions of the system, which were collected via a post-study questionnaire and a usage diary.

2. Related work

Wearable activity systems—capable of tracking steps, heart rate, and exercise routes in real time—have been increasingly considered as promising tools for promoting physical activity. Persuasive technology provides a theoretical foundation needed to shift these devices from passive trackers into active interventions. As Fogg defines it, persuasive technology involves "interactive computing products designed, researched, and analyzed for the purpose of changing people's attitudes or behaviors" [6]. This concept elevates computers from mere tools to persuaders that can shape behaviors. Early research in this area focused on conventional digital environments like websites and desktop

applications. However, as wearable technologies become increasingly mature, their high-tactility characteristics have opened up new potential for persuasion.

Among the various theoretical frameworks, the Fogg Behavior Model (FBM) offers a view of how behaviors are actually triggered. Drawing on this model, Yuasa et al. proposed an exercise promotion method that examines time-series step data to assess a user's activity level. When activity is higher, it is interpreted as a sign of greater user capability, which the system then uses to tailor the timing and mode of behavioral triggers [8]. Self-Determination Theory (SDT) explores the psychological mechanisms that why behavior can be sustained. Jang and Kim qualitatively analyzed Fitbit user reviews and revealed that users' interactions with the devices tend to evolve from extrinsic to intrinsic motivation over time. This supports SDT's core idea that intrinsically motivated behavior is more sustainable in the long run [9].

Grounded in the theoretical foundations, researchers have turned their focus to specific, actionable persuasive strategies. Today, the strategies most widely discussed in the context of wearable exercise systems include goal setting, self-monitoring, social influence, gamification, reminders, and suggestions. Goal-setting theory gives a practical useful framework for enhancing task motivation and performance across many settings. Ho et al. conducted a two-phase goal-setting trial with the community elderly, in which the intervention group increased their daily step goals during the latter phase. The results indicated that wearable activity trackers incorporating progressive goal setting can improve physical activity levels in the elderly [10]. Self-monitoring is a central strategy in many physical activity programs. In their systematic review and meta-analysis, Compernelle et al. found that self-monitoring interventions reduce total and occupational sedentary time in the short term, but only when self-monitoring tools are used and the intervention is exclusively focused on sedentary behavior [11]. Social influence is an important psychological factor in human decision-making, and this is directly mirrored in the social features of wearables. A large-scale study of Fitbit leaderboard data found that leaderboards help increase average daily steps, but they actually have opposite effects on sedentary users versus highly active ones [12]. Gamification has become one of the most widespread design strategies in wearable devices. Chang et al. found that most wearables incorporate game elements such as badges, points, levels, and virtual rewards into exercise scenarios [13]. Reminders and suggestions are among the strategies with the lowest cognitive load, and are also common in everyday wearable use. Research showed that interventions combining wearables with mobile applications produce better long-term outcomes. This is because the automatic data capture of wearables removes the burden of manual entry, enabling the "reminder-feedback" persuasive loop to operate sustainably at low user cost [14]. Notably, the effectiveness of these persuasive strategies varies across individuals, and hence one-size-fits-all design cannot adequately address user heterogeneity. As a result, personalized persuasion is emerging as a promising frontier in this field. A systematic

evaluation of smartwatch users revealed that a gap exists between the game elements users preferred and those that actually motivate them to exercise. This suggests that tailoring design based on users' stated preferences is insufficient. Indeed, motivational modeling and behavioral data could be incorporated for effective dynamic optimization [15].

While existing research has built a solid foundation for applying persuasive technology to wearable activity devices, several areas remain open for improvement. At the design level, many studies remain at the conceptual or simulation stage. There has been insufficient research that translates theoretical frameworks into operational systems and validates them in the field. Moreover, most have focused on the effects of single strategies, with limited systematic exploration of the interactions, combinations, and integrative design among different strategies. In terms of evaluation, studies that link subjective experiential data with objective behavioral measures are still scarce. This gap limits our understanding of how these strategies actually function. Additionally, there are still limited empirical evidence on personalized persuasion, particularly regarding the evaluation of such systems in real-world contexts. To address these gaps, this study presents the design, implementation, and evaluation of a wearable-based exercise promotion system that integrates multiple persuasive strategies, offering a reference from theory to practice in this domain.

3. Design of persuasive wearable system

3.1. Wearable exercise system

Designed for individuals willing and able to exercise but lacking sustained practice, the wearable system operates through three modules: a wearable strap, an interactive mobile application, and a data server (Figure 1).

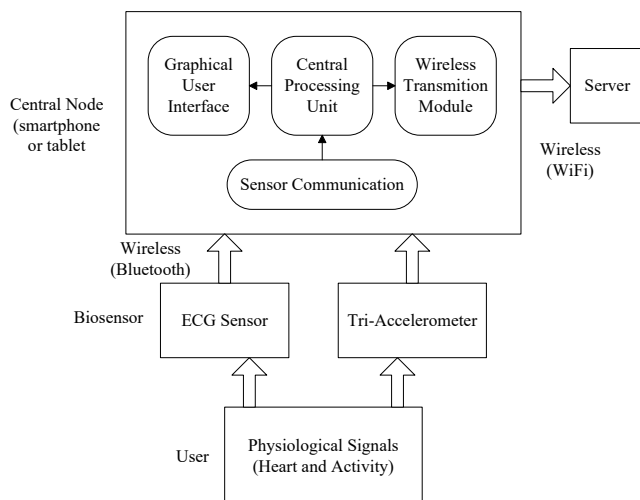


Figure 1. Architecture of the wearable exercise system

The wearable strap

The device employed an X-band chest strap fabricated from polyester fabric, which integrated three ECG sensors and a tri-axial accelerometer to monitor the user's cardiac and physical activities, respectively (Figure 2). The sensor data collected were transmitted to a signal processing unit through digital yarns and subsequently wirelessly relayed to mobile devices, such as smartphones and tablets, via a Bluetooth transmitter.

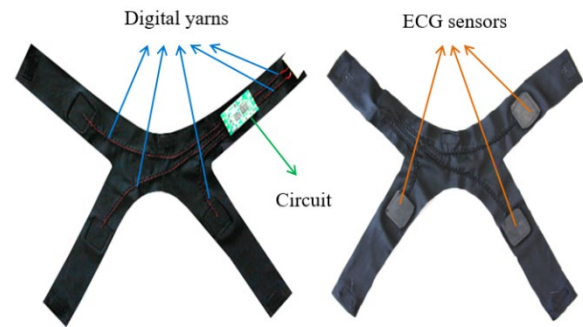


Figure 2. The strap with ECG sensors and accelerometer

The interactive application

The mobile device received the sensed data and transmitted it to the interactive application (Figure 3). Deployed on Android-based operating systems, the application interpreted the sensed data, then extracted parameters related to heart rate (HR) and physical activity metrics (i.e., step count and distance covered). These parameters were presented to users via real-time visual feedback, enabling on-demand access at any time. Additionally, the application established wireless communication with a remotely deployed server to implement bidirectional data transmission.



Figure 3. Main screen of the application

The server

The server architecture comprised distinct modules for receiving, storing, and processing sensed data, alongside a Service Oriented Architecture (SOA) module that facilitated access to wellness services. The SOA component was designed to handle standard messages. Specifically, the client transmitted SOAP messages via HTTP to request services from the server-side SOA component, which then generated and returned SOAP response to the client.

3.2. Persuasive strategies

Oinas-Kukkonen and Harjumaan proposed the Persuasive Systems Design (PSD) model, which delineates four categories of persuasive principles, namely primary task support, dialogue support, system credibility support, and social support [16]. The present study explored the application of PSD model in wearable exercise systems, translating abstract persuasive design principles into concrete implementation strategies (Figure 4).



Figure 4. Persuasive strategies and their implementation

Goal setting

Previous studies have demonstrated that specific and challenging goals, in comparison to easy goals or vague, abstract ones (e.g., "do your best"), can consistently enhance

individuals' performance levels [17,18]. Consequently, goal setting exhibits the potential to facilitate successful behavior change [19].

Within the proposed system, exercise-related metrics (e.g., calories burned) were designated as workout goals, which were set and tracked on a weekly cycle with a dual support mechanism: system-assigned goals and self-set goals. Specifically, system-assigned goals were default values generated from user profile data and historical exercise data, reflecting the weekly recommended calorie expenditure to maintain health; self-set goals enable users to customize targets manually, primarily to support weight loss objectives. Figure 5 presents the interface for weekly exercise goal setting, which adopted the system-assigned goal mechanism.

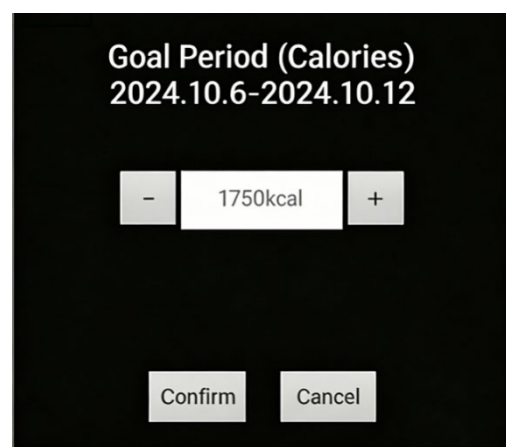


Figure 5. Goal setting

Personal awareness

Feedback provides individuals with evaluative information that enables the adjustment or maintenance of their performance [20]. Interventions such as self-monitoring have been verified to facilitate behavioral change and improve self-efficacy [21]. Additionally, the positive effects of goal setting on behavioral change can be amplified by progress feedback toward preset goals [18]. Accordingly, providing rational, accessible information on individuals' behaviors and goal progress is valuable [22].

Three functions were developed to monitor and access exercise-associated data, namely performance feedback, goal progress, and exercise history. The application delivered real-time HR and walking-related metrics (i.e., step count and distance covered) to users as performance feedback (Figure 6). Post-exercise, users may also access session-specific summary data (e.g. total steps and distance) corresponding to the completed workout (Figure 7).



Figure 6. Real-time exercise feedback



Figure 7. Exercise results

The application generated an exercise calendar based on users' exercise history data stored on the server, where users can review their exercise progress toward the preset goals. Figure 8 presents the exercise calendar for a specific month, in which blank entries, cheer-up badges, and star trophies represent no exercise, partial daily goal achievement, and daily goal completion, respectively.



Figure 8. Exercise calendar

Users can further review trend information regarding their historical exercise behaviors. Figure 9 presents the exercise performance for a specific month. On the left side of the figure, key exercise metrics are summarized: total duration, active days, calories burned, total steps, total distance, and average daily distance. On the right side, two graphs respectively display daily exercise goal attainment (against the 255kcal daily goal) and daily exercise distance (with a 600-meter limit due to interface layout constraints).

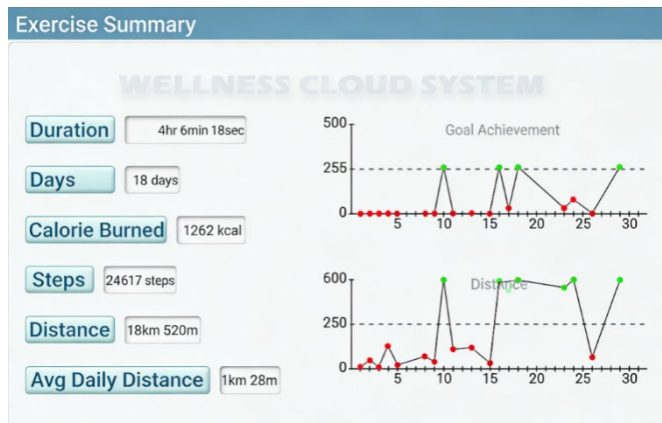


Figure 9. Exercise history

Social influence

Self-presentation refers to a consciously practiced form of impression management during interpersonal interactions, in which the motivation to project a positive image to others may drive behavioral changes [23]. Research has demonstrated that collaborative work typically facilitates greater change in individual attitudes and behaviors [6]. Social pressures exerted by others affect a broad range of life choices, including physical activity engagement. Accordingly, social influence has been recognized as a positive contributor to the increase and maintenance of physical activity [24].

Our system incorporated support for social network services, enabling users to identify workout partners and establish social groups. To add a new member to a social group, users submitted a request to the server, which approved the request only after confirmation from the invitee. Users in the same social group may access the exercise performance rankings of all group members. Figure 10 presents a partial ranking for a designated social group, which is calculated based on weekly caloric expenditure, and incorporates data on individual exercise goals, calories burned, and goal achievement status.

Reinforcement

Reward strategies can attract users, enhance the engagingness of target behaviors, and reinforce their adherence to preset goals [25]. Studies have shown that rewards exert a positive effect in computerized environments. Specifically, individuals who receive computerized rewards exhibit more positive responses compared to those who do not [6]. Accordingly, integrating rewards with goal-setting strategies can motivate users to pursue and accomplish preset goals, allowing them to gain recognition through goal attainment and be influenced by positive feedback.

In the exercise calendar, rewards were allocated based on two dimensions: progress toward preset goals (denoted by a cheer up badge) and the completion of daily goals (denoted by a star trophy), as shown in Figure 8. In the exercise performance ranking, the progress of weekly exercise goal attainment was represented by the number of illuminated stars out of a total of 10, as shown in Figure 10.

RANKING!!			
 15418583 ★★★★★★★★★	Calorie Goal : 1,925kcal	Calorie Burned : 515.4kcal	Goal Achievement : 27%
 Sanin ★★★★★★★★★	Calorie Goal : 2,100kcal	Calorie Burned : 459.1kcal	Goal Achievement : 22%
 kht ★★★★★★★★★	Calorie Goal : 1,750kcal	Calorie Burned : 323.0kcal	Goal Achievement : 18%
 oqhee0097 ★★★★★★★★★	Calorie Goal : 1,750kcal	Calorie Burned : 296.3kcal	Goal Achievement : 17%
 pys5143 ★★★★★★★★★	Calorie Goal : 1,750kcal	Calorie Burned : 191.4kcal	Goal Achievement : 11%
 dong1989 ★★★★★★★★★	Calorie Goal : 1,750kcal	Calorie Burned : 173.1kcal	Goal Achievement : 10%
 stjmh ★★★★★★★★★	Calorie Goal : 2,275kcal	Calorie Burned : 173.1kcal	Goal Achievement : 8%

Figure 10. Exercise performance ranking

Suggestion and reminder

Suggestion technology is defined as a technological approach involving active notifications that prompt individuals to engage in behaviors they would not otherwise initiate [26]. In persuasive technology, reminder functionalities are widely employed to prompt users to complete priority tasks at optimal timings, whereas recommendation features guide users toward more positive behavioral choices by delivering targeted actionable guidance [27].

The developed system incorporated an exercise reminder that notifies users when nearing their preset exercise schedules; additionally, users can access personalized weight recommendations as well as tailored guidance on exercise management. As shown in Figure 11, the system interface presents the user's current weight, Body Mass Index (BMI), and exercise-related recommendations. Specifically, due to variations in physical constitution, the BMI classification standard employed in this system adopted the Asian criteria, which define a relatively lower threshold compared to the international standards [28].

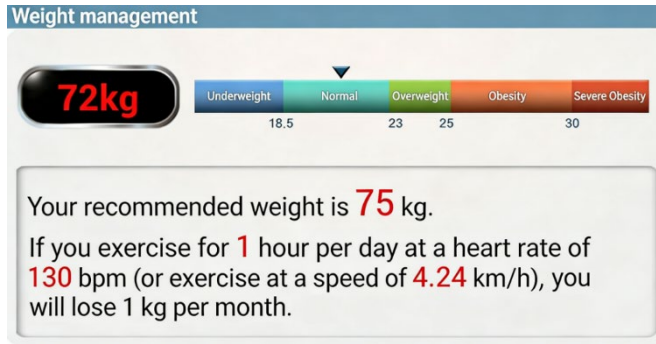


Figure 11. Exercise and weight recommendation

Enjoyment interaction

By framing desired behaviors as enjoyable and engaging, individuals' participation in and adherence to health-promoting activities may be enhanced. Interaction with a compelling system not only elevates its attractiveness to users, but also sustains their engagement over extended periods [29].

Music exerts positive effects during exercise, and is frequently integrated into the exercise routines of many individuals, serving to improve mood and reduce the monotony of exercise [30]. Accordingly, a music feature was incorporated into the developed system to enhance users' exercise motivation. When activated, the application will automatically play music during the user's exercise session.

3.3 Adaptive goal adjustment

By dynamically adjusting exercise goals, users can gradually increase their activity levels without becoming overburdened. Based on users' historical exercise behaviors and real-time feedback, this study employed a contextual multi-armed

bandit (C-MAB) approach combined with the ϵ -greedy policy to guide goal adjustment decisions. In particular, the C-MAB approach can track changes in user requirements and scenarios, enabling it to provide timely, adaptive interventions. This makes it well-suited for mHealth settings [31]. In addition, the ϵ -greedy algorithm offered low computational complexity, strong interpretability, exploration-exploitation trade-off, simple parameterization, and the ability to support multiple intervention actions, thereby qualifying it for mHealth pilot studies and small-sample scenarios [32].

The model used the user's exercise state as the input, generated a goal adjustment strategy as the output, and relied on the exercise feedback as the learning signal. We further introduced a decision-variability-aware mechanism along with a dual exploration-rate switching strategy. The model consisted of six modules: a state space, an action space, a reward function, a decision variability assessment, an adaptive exploration rate strategy, and a Q-value update mechanism. These modules collaborated to form a closed-loop learning system. The detailed implementation was as follows:

(1) State Space

Equation (1) shows the feature vector encompassing the state space. This includes static characteristics that reflect baseline exercise ability (i.e., age, gender, and BMI), exercise data that describe the present exercise load (i.e., step count, energy expenditure, duration, and HR), the current exercise goal that serves as the decision baseline, and historical trend features that capture recent goal completion status.

$$S_t = [\text{Age}, \text{Gender}, \text{BMI}, \text{Steps}_t, \text{Energy}_t, \text{Duration}_t, \text{HR}_t, T_t, \text{Trend}_t]$$

$$\text{Trend}_t = \begin{cases} 0, & t < 0 \\ C_{t-1} - C_{t-2}, & t = 3 \\ C_{t-1} - C_{t-3}, & t \geq 4 \end{cases}$$

$$C_t = \text{Actual}_t / T_t$$

(1)

Where T_t represents the preset exercise goal for day t , C_t denotes the rate of goal achievement for day t , and Actual_t represents the actual amount of exercise completed by the user on day t (consistent in unit with T_t).

(2) Action Space

Five standardized goal adjustment actions are established: significantly decrease, slightly decrease, maintain, slightly increase, and significantly increase, as indicated in Equation (2). A percentage-based adjustment approach is used, along with a lower bound on the goals, to improve personalization and strengthen motivation to exercise.

$$A_t \in \{0, 1, 2, 3, 4\} \quad (2)$$

(3) Reward Function

Equations (3) presents the reward function consisting of a completion reward and a stability reward. The completion reward is designed to direct the model toward optimizing goals and is calculated using the goal achievement rate. Specifically, a bonus of +10 is awarded when the

achievement rate falls within range of 80% to 120%. A penalty of -5 are applied for rates below 50% or above 150%. For the intermediate ranges (50%–80% and 120%–150%), the reward scales linearly with the achievement rate. Meanwhile, the stability reward is determined based on variations in the recent achievement rates, aiming to promote consistent and stable exercise behavior.

$$R_t = R_{\text{comp},t} + R_{\text{stab},t}$$

$$R_{\text{comp},t} = \begin{cases} -5, & C_t < 0.5 \text{ or } C_t > 1.5 \\ 50(C_t - 0.5) - 5, & 0.5 \leq C_t \leq 0.8 \\ 10, & 0.8 \leq C_t \leq 1.2 \\ -50(C_t - 1.2) + 10, & 1.2 \leq C_t \leq 1.5 \end{cases}$$

$$R_{\text{stab},t} = \begin{cases} 5, & \max(C_{t-2}, C_{t-1}, C_t) - \min(C_{t-2}, C_{t-1}, C_t) < 0.2 \\ -3, & \max(C_{t-2}, C_{t-1}, C_t) - \min(C_{t-2}, C_{t-1}, C_t) > 0.5 \\ 0, & \text{others} \end{cases} \quad (3)$$

(4) Decision Variability

Decision stability is measured using the information entropy of the recent action selection distribution. A higher variability indicates more dispersed recent action selection and greater decision uncertainty, thus demanding more exploration. To reduce the long-term effects of early exploration, a sliding window method is used, which keeps only the action selection records from the most recent W days. To begin, the Equation (4) shows the action selection count vector by day t .

$$N_t^{(w)} = [n_0^{(w)}, n_1^{(w)}, n_2^{(w)}, n_3^{(w)}, n_4^{(w)}] \quad (4)$$

where $n_i^{(w)}$ denotes the count of action i within the window. Equation (5) gives the total selection count within the window.

$$N_{\text{total}}^{(w)} = \min(t, W) \quad (5)$$

Using the total counts and the counts within the window, Equation (6) determines the probability of selecting each action.

$$p_i = n_i^{(w)} / N_{\text{total}}^{(w)}, \quad i=0, 1, 2, 3, 4 \quad (6)$$

When an action has not been selected within the window, $p_i=0$. Afterwards, the information entropy is used to quantify how dispersed the action selection distribution is:

$$H_t = - \sum_{i=0}^4 \begin{cases} p_i \ln(p_i), & p_i > 0 \\ 0, & p_i = 0 \end{cases} \quad (7)$$

Equation (8) specifies the decision variability using the normalized information entropy.

$$\text{Var}_t = \begin{cases} 0.5, & t < 5 \\ H_t / \ln(5), & t \geq 5 \end{cases} \quad (8)$$

where $\ln(5) \approx 1.609$ is the maximum entropy when the five actions are equally likely. When $t \geq 5$, H_t is calculated using

the window-valid data; when $t < 5$, the action selection count is not sufficient to estimate variability, thus Var_t is set to 0.5.

(5) Dual Exploration Rate

The exploration rate changes dynamically between two levels depending on the measured variability in decisions. Equation (9) lays out the exact switching rules.

$$\varepsilon_t = \begin{cases} \varepsilon_{\text{high}}=0.7, & \text{Var}_t > 0.6 \\ \varepsilon_{\text{low}}=0.2, & \text{Var}_t < 0.4 \\ \max(\varepsilon_{\text{low}}, \varepsilon_{t-1}-\delta), & \text{others} \end{cases} \quad (9)$$

A high exploration rate is used when the decision variability is high, while a low exploration rate is applied when the variability is low. For intermediate levels of decision variability, a decay step δ (with a default value of 0.02) is utilized to slowly reduce the exploration rate, so that the exploration rate smoothly converges toward an exploitation preference.

Based on derived exploration rate, the model employs an ε -greedy policy for action selection to balance the exploration and exploitation, as shown in Equation (10).

$$A_t = \begin{cases} \arg \max_A Q(A), & \text{rand}(0, 1) \geq \varepsilon_t \\ \text{rand}(0, 4), & \text{rand}(0, 1) < \varepsilon_t \end{cases} \quad (10)$$

(6) Action-Value Function

To evaluate the expected long-term reward of each action, the model updates the Q -values using an exponential moving average (EMA) approach, as shown in Equation (11). A learning rate α (defaulting to 0.1) is introduced to smoothly adjust the historical values based on the current reward.

$$Q(A_t) = Q(A_t) + \alpha(R_t - Q(A_t)) \quad (11)$$

Figure 12 illustrates the iterative workflow of the model. The process commences with initialization, where the initial exercise goal, initial action values (Q -table), action selection count vector, and initial exploration rate are configured. Once the user completes the current exercise goal, a new iteration begins. First, the model constructs the state representation by aggregating the user's static features, exercise data, current goal, and historical trend. Second, the recorded actual exercise data is utilized to compute the goal achievement rate and total reward, which subsequently update the Q -value of the executed action. Third, the model calculates decision variability from the action selection count vector and adaptively tune the exploration rate. Finally, guided by the updated Q -table and exploration rate, the ε -greedy policy selects the subsequent action and adjust the exercise goal accordingly. This cycle repeats, enabling continuous model iteration and dynamic goal optimization.

4. Evaluation of persuasive strategies

A user-centric empirical study was designed to explore users' perceptions of the system through a one-week field use. Participants' experiences of the system's persuasive design, as

well as their attitudinal reactions to the system, were evaluated using a post-study questionnaire and a usage diary.

4.1 Participants

25 participants from the student and faculty populations of university were recruited to pilot and evaluate the developed system. The sample consisted of 11 males and 14 females with ages ranging from 20 to 60 years. Participant characteristics are presented in Table 1.

Table 1. Participant Characteristics (N=25)

	Gender	Age (years)	Weight (kg)	Height (m)
Mean	0.44	37.92	61.84	1.68
SD	0.51	10.90	11.18	0.09
Min	0	21	45	1.56
Max	1	58	80	1.82

Note: 0=female, 1=male

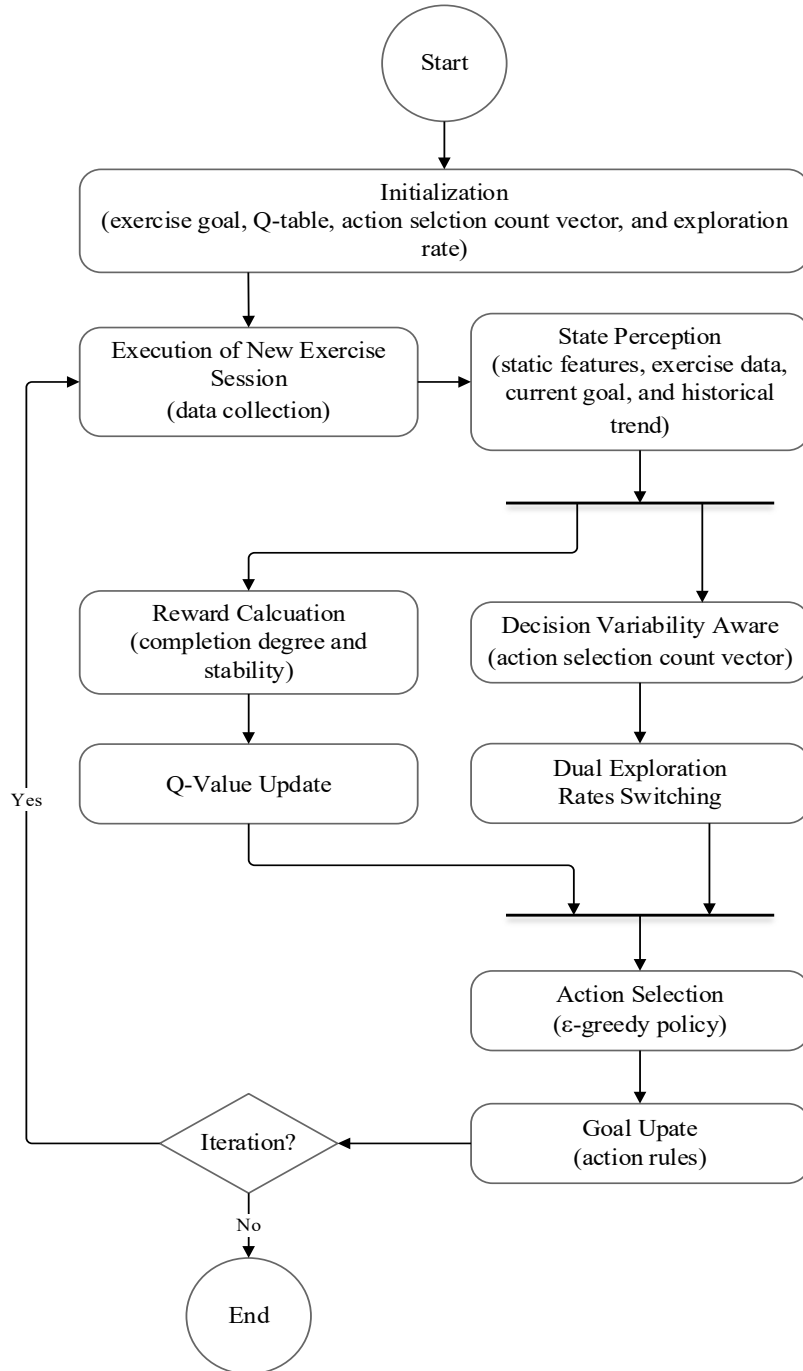


Figure 12. Workflow of the goal adjustment model

All of the participants possessed university degrees, with the majority ($n = 20$) holding bachelor's degrees and 5 having earned master's degrees or higher. Based on BMI calculations derived from participants' self-reported height and weight data, 2 individuals were categorized as underweight ($BMI < 18.5$), 16 as having a normal weight ($18.5 \leq BMI < 23$), and 7 as overweight or slightly obese ($BMI \geq 23$). In terms of self-assessed health status, most participants rated their health as at least “good”: 3 reported “fair”, 6 “good”, 14 “very good”, and 2 “excellent.” Regarding regular exercise behavior, the proportion of participants engaging in routine exercise was relatively low: 5 reported exercising “seldom”, 14 “sometimes”, 5 “somewhat regularly”, and 1 “regularly”. Participants further rated their level of experience with smartphone applications using a 5-point Likert scale, where a score of 1 represented “no experience” and 5 denoted “very

experienced.” The participants exhibited a high frequency of smartphone application usage ($M = 4.52$).

4.2 Procedure

The field study consisted of three sessions and a one-week in-situ use of the system (Figure 13). During the first session, participants were briefed on the objectives and procedures of the field study, and completed a pre-study questionnaire investigating their demographic information, health status, exercise frequency, and technological familiarity. Subsequently, participants installed the developed application on their personal smartphones and received guidance on the proper wearing of the dedicated strap and the operation of the installed application.

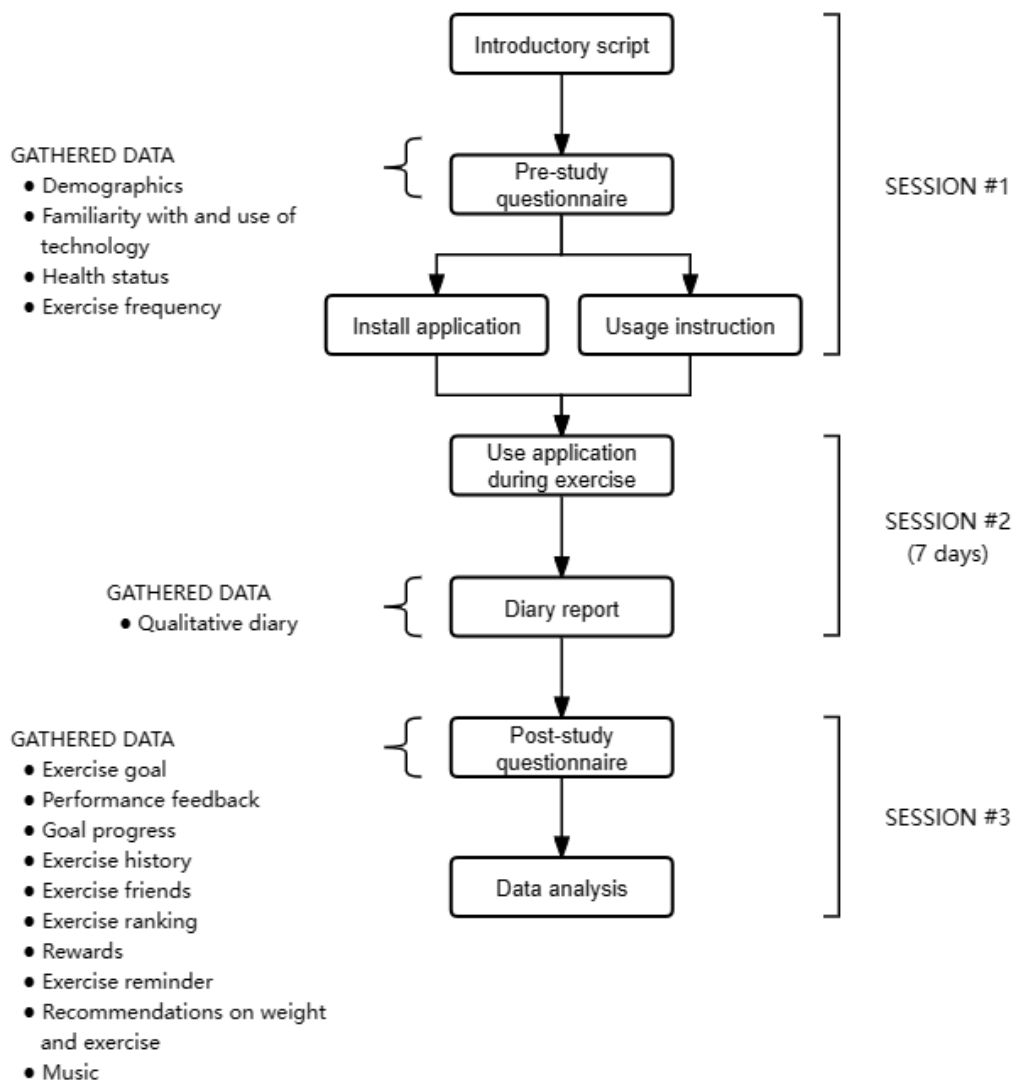


Figure 13. Method design including procedures and gathered data

In the second session, conducted seven days following the initial session, participants were instructed to complete ten predefined user tasks using the developed system (Table 2). These ten tasks were designed to elicit participants' evaluations of the persuasive strategies implemented in the system. Additionally, participants could customize tasks based on their daily routines and preferences. For the collection of qualitative data, participants were further requested to maintain a usage diary documenting their system interaction experiences, perceived benefits, identified limitations, and recommendations for system optimization.

In the third session, participants completed a post-study questionnaire to report tasks experiences and subjective perceptions of system functionality. This questionnaire was designed to collect data regarding the persuasive design aspects of the developed system, including exercise goals, performance feedback, goal progress, exercise history, workout companion, exercise ranking, rewards, weight and exercise recommendations, and music integration. In addition, two standalone items were included to quantify participants' perceptions of the system's persuasive efficacy, specifically examining its impact on promoting exercise participation and the self-reported likelihood of regular system usage.

Table 2. User Tasks

No	Task	Related Strategies
01	Set personal demographic information (i.e., gender, weight, and height).	Goal setting
02	Establish personalized weekly exercise goals within the system.	
03	Perform walking-based physical exercise to fulfill the preset weekly goals.	
04	Optionally, view progress toward the preset exercise goals.	Personal awareness
05	Optionally, access a summarized report of historical exercise records.	
06	Optionally, explore and utilize the system's workout companion function.	Social influence
07	Optionally, check rewards accrued by oneself and one's workout companions.	Reinforcement
08	Optionally, retrieve the system-generated personalized recommendations for exercise regimens and weight management.	Suggestion
09	Optionally, activate and test the system's exercise reminder function.	Reminder
10	Optionally, enable and experience the integrated music playback function during exercise.	Enjoyment interaction

4.3 Data analysis

After the in-situ system use, 24 usage diaries were collected, and all participants completed the post-study questionnaire. We further examined how participants engaged with the system's persuasive features and how such engagement shaped their subjective perceptions of the system.

To evaluate the persuasiveness of the system, persuasiveness ratings were derived from participants'

feedback on the persuasive strategies, which were rated on a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree). The mean rating across all participants was calculated for each strategy (see Table 3). Participants showed the highest rating for Strategy #3 (social influence, 4.41), followed by Strategy #1 (goal setting, 4.39). Strategy #4 (reinforcement, 4.28) ranked third, while Strategy #2 (personal awareness, 4.23) ranked fourth. Strategy #6 (enjoyment interaction 3.82) and Strategy #5 (suggestion and reminder, 3.44) yielded the lowest ratings.

Table 3. Descriptive Statistics of Persuasive Strategies

Persuasive Strategies		Mean	Averaged Mean	SD
1. Goal setting	a. Goal support exercise adherence	4.44	4.39	.814
	b. Goal criteria are satisfactory	4.19		.834
	c. Will continue using goal function	4.53		.640
2. Personal awareness	a. Real-time performance feedback is useful	4.06	4.23	1.063
	b. Daily goal progress is helpful	4.44		.727

Persuasive Strategies		Mean	Averaged Mean	SD
3. Social influence	c. History exercise data is valuable	4.19		.911
	a. Workout partner feature is beneficial	4.50	4.41	.632
	b. Rankings motivate exercise	4.63		.619
	c. Ranking criteria are appropriate	4.13		.719
4. Reinforcement	d. Will continue using workout partner feature	4.38		.719
	a. Rewards bring satisfaction	4.25	4.28	.683
5. Suggestion and reminder	b. Expect to earn exercise rewards	4.31		.704
	a. System recommendations are useful	3.94	3.44	1.181
6. Enjoyment Interaction	b. Will continue using reminder function	2.94		.998
	a. Exercise music is desirable	3.69	3.82	1.250
	b. Will continue using music function	3.94		1.063

Since six persuasive strategies were adopted for the system's design and implementation, exploring the effects of these strategies on the system's persuasiveness is critical. We therefore employed two measurement variables to assess the system's persuasiveness, as follows:

- (i) Measurement of Subjective Persuasiveness: participants' perceptions of whether the system motivates exercise engagement.
- (ii) Measurement of Behavioral Outcome: participants' feedback on their willingness to continue using the system on a regular basis.

Since the data satisfied the assumptions of linearity and normality for continuous variables, Pearson correlation analysis was employed to examine the correlations between these two measurement variables and each of the six persuasive strategies (Table 4). All correlations were positive, demonstrating that each of the six persuasive strategies exerted a positive influence on the system's persuasiveness. Furthermore, among the 26 correlations, three were significant at the 0.01 level, thirteen were significant at the 0.05 level, and the remaining ten were marginally significant ($0.05 < p < 0.098$), with potential for statistical significance if the sample size were expanded.

Table 4. Significant Correlations between Measurement Variables and Persuasive Strategies

Persuasive Strategies		Persuasiveness 1. Motivates exercise	Outcome 2. Continues regular use
1. Goal setting	a. Goal support exercise adherence	.519*	.494
	b. Goal criteria are satisfactory	.539*	.659**
	c. Will continue using goal function	.603*	.538*
2. Personal awareness	a. Real-time performance feedback is useful	.488	.673**
	b. Daily goal progress is helpful	.428	
	c. History exercise data is valuable	.494	.638*
3. Social influence	a. Workout partner feature is beneficial	.438	
	b. Rankings motivate exercise		.535*
	c. Ranking criteria are appropriate	.520*	.568*
	d. Will continue using workout partner feature	.481	.729**
4. Reinforcement	a. Rewards bring satisfaction	.498*	.637*
	b. Expect to earn exercise rewards		.450
	a. System recommendations are useful	.446	.535*

Persuasive Strategies		Persuasiveness	Outcome
		1. Motivates exercise	2. Continues regular use
5. Suggestion and reminder	b. Will continue using reminder function		.573*
6. Enjoyment Interaction	a. Exercise music is desirable	.404	.613*
	b. Will continue using music function	.449	

Correlation is significant at *0.05 and **0.01 levels (two-tailed)

Correlation may be significant after increasing participants ($0.05 < p < 0.098$)

Figure 14 presents a correlation heatmap illustrating the relationships between the two measurement variables and all implemented persuasive strategies. Most goal-setting variables exerted significant effects on both measurement variables, though goal support exercise adherence correlated only weakly with continued regular use. Regarding personal awareness, the usefulness of real-time feedback and historical data both demonstrated moderate correlations with continued regular use. All three variables under this strategy showed weak correlations with exercise motivation. Appropriate ranking criteria exhibited moderate correlations with both measurement variables. Rankings motivate exercise and the workout partner feature showed moderate and strong correlations with continued regular use, respectively. The workout partner feature was weakly correlated with exercise motivation.

Reward satisfaction exhibited moderate correlations with both measurement variables. However, reward expectancy showed a weak correlation with continued regular use. Recommendations and reminders were both moderately correlated with continued use, though recommendations showed a weak correlation with exercise motivation. Exercise music was moderately correlated with continued regular use, but weakly correlated with exercise motivation.

Based on average persuasiveness ratings, the top three highest-rated strategies—social influence ($M = 4.41$), goal setting ($M = 4.39$), and reinforcement ($M = 4.28$)—demonstrated moderate-to-strong correlations with the outcome measures. The lower-rated strategies—personal awareness ($M = 4.23$), enjoyment interaction ($M = 3.82$), and suggestion and reminder ($M = 3.44$)—showed weaker or non-significant effects (see Table 3).



Figure 14. Correlation heatmap between measurement variables and persuasive strategies

4.4. User attitudes

We next report participants' subjective feedback from the usage diaries, categorized according to the six persuasive strategies, as a qualitative supplement to the preceding quantitative correlation results. To analyze the qualitative responses, we adopted a directed content analysis procedure. Specifically, the process involved three steps: first, the six predetermined persuasive strategies were used as the initial coding framework; second, participants' comments were coded and categorized according to these strategies; and third, key insights and representative quotes were identified to capture participants' perceptions of each strategy.

Goal setting

A total of 22 participants set exercise goals throughout the one-week study period. The majority adopted the default goal ($n = 16$), while 3 participants set lower goals and

another 3 set higher goals relative to the default. On average, participants achieved 22% of their respective goals.

23 participants reported that the goal-setting function helped them adhere to exercise, as exemplified by the comments “...it explains how to set goals, which makes it easier to stay consistent with exercise” and “After setting a weekly goal, I now get off the bus one stop earlier and walk home every day.” Additionally, 22 participants approved of the goal-specifying criteria (i.e., calories burned and exercise-induced weight loss) and expressed willingness to keep using the goal-setting feature to support their workout routines.

3 participants suggested the need for more flexible options for goal-setting, including “It would be preferable to customize the goal period independently” and “Seven days is too short; I'd rather have a longer period, like 15 days.”

Personal awareness

Most participants perceived the personal awareness-related features as helpful. Specifically, 20 participants found the exercise monitoring and real-time performance feedback features useful, 22 participants considered the goal progress review helpful, and 16 participants valued the historical exercise records.

They showed interest in tracking how well they were performing their exercise, stating: *"I like knowing how long I've walked and how many calories I've burned"* and *"It's nice to monitor my daily workout volume."* A significant number of participants ($n = 19$) gave positive feedback on the real-time visual performance feedback. For example, *"It's good to track my exercise duration, calories burned, distance traveled, and steps taken"* and *"I can monitor my workout volume using several different measures like time, distance, and steps."*

Most participants ($n = 22$) favored the visual cues for pending and completed goals, such as: *"I think it's clear to see my progress through the colorful indicators..."* They also valued the system's goal review data, with comments including *"I previously had no idea about my weekly exercise volume, but this app makes it clear..."* and *"It motivates me to exercise more if I didn't do enough the day before."*

Additionally, 20 participants reported positive views of the cumulative statistics for historical performance, as illustrated by: *"I like the daily, weekly, and monthly summaries—they help me check my exercise status in detail"* and *"Nice trending graph."*

Several participants questioned the accuracy of the system's measurements, remarking, *"The distance measured is less than the actual one..."* and *"It seems to make no distinction between walking and running."* 2 participants requested additional exercise monitoring functions, such as *"It would be better to have a pause function for when I need to stop temporarily..."* Some participants also found the goal progress display on the exercise calendar page confusing, stating: *"It would be nice to view my progress intuitively, e.g., similar to the workout partners' rankings"* and *"The exercise scores are hard to understand."*

Social influence

Most participants held positive attitudes toward the social influence-related features. 22 participants joined the exercise competition activity, and they acknowledged that workout partners provided positive motivation, and that the competition ranking between partners acted as an effective incentive, as exemplified by comments: *"One nice thing about the app is the competition—I compared my exercise data with others this week"*, *"Although I don't enjoy exercise, friend rankings boost my motivation to work out"* and *"I tried really hard to beat my friends and get a better ranking position."*

20 participants approved of the ranking criterion (i.e., calories burned through exercise), and 22 expressed willingness to keep using the workout partner function on a regular basis. 3 participants suggested that the app should

display their own competition ranking position prominently, stating: *"My ranking position isn't highlighted; I have to count from the top to figure out I'm in fifth place"* and *"There are just too many people on the ranking list, so it's hard to locate my own position."* 2 participants proposed adding extra features to facilitate user-to-user interaction, such as *"It would be better if the app had a comment function for users to communicate."*

Reinforcement

22 participants reported expectations of earning rewards through the system, while another 22 expressed positive feelings if they could meet their exercise goals. Two participants put forward suggestions regarding how rewards are presented; representative comments included: *"On the ranking page, the icons representing the top three should be distinct from those of other users..."*

Suggestion and reminder

19 participants held positive attitudes toward the exercise and weight recommendations provided by the system, with representative comments including: *"I can view the required exercise volume in the weight management..."* and *"The weight management feature works really well for me."* Another 6 participants requested more detailed recommendations.

Participants exhibited mixed reactions to the exercise reminder function. For instance: *"It reminds me to open the app around the time I planned to exercise, which is very effective"* and *"The reminders annoyed me."* 8 participants found the reminder helpful, and 6 expressed willingness to keep using it regularly. 5 participants hoped for more diverse reminder types, exemplified by comments: *"I want the app to remind me every ten minutes; it helps me keep aware of my exercise time"* and *"It would be better to have voice reminders..."*

Enjoyment interaction

16 participants considered the in-exercise music playback feature desirable and enjoyable. 17 participants perceived improved exercise efficiency when listening to music during their workouts. 19 participants expressed willingness to keep using the music playback function regularly. Participants held favorable views of the music feature, stating: *"I really like listening to music while exercising"* and *"...music playback makes exercise more engaging."* Several participants requested additional music player functions, such as: *"I would be great if the app could find music saved on the SD card"* and *"I want more control of the music player, like being able to pick certain songs."*

5. Discussion

The quantitative and qualitative findings showed that participants generally viewed the system positively. Most indicated that it effectively increased their physical activity

levels and expressed interest in using it regularly. Quantitatively, the average persuasiveness rating across all six strategies reached 4.1 on the Likert scale, which supports the logic of our design and implementation approach. Notably, three strategies—social influence, goal setting, and reinforcement—were significantly correlated with effective exercise motivation, reflected by their higher average persuasiveness rating of 4.36. In addition, all six strategies correlated significantly with participants' reported likelihood of future regular system use. However, personal awareness, enjoyment interaction, and suggestion demonstrated weaker associations with exercise motivation, suggesting that more research is needed to better understand the specific motivational function of these elements. Below, we discussed possible reasons for the observed effects of each strategy by combining our results with evidence from prior studies, and we offered targeted design recommendations to guide the development of future persuasive systems aiming at encouraging physical activity.

5.1 Goal setting

Goal setting played a key role in encouraging both physical activity and continued use of the system. This suggests that participants with higher goal completion rates experienced greater motivation to maintain exercise engagement, which matches earlier findings that setting specific goals can have long-term beneficial effects on physical activity and psychological outcomes [33]. Achievable and realistic goals helped participants feel a sense of accomplishment, strengthening their drive to continue exercising. This is supported by actionable goals, such as 2000 daily step increments, which effectively enhanced adherence to physical activity [34]. Moreover, goal-specifying criteria (i.e., calories burned and exercise-induced weight loss) were positively linked to both exercise motivation and intention to use the system. This provides further evidence that participants were more likely to adopt and actively engage with specific, measurable goals [18].

Qualitative findings also revealed potential design limitations that may have reduced the motivational impact of goals. Participants' requests for more flexible goal options indicate that the system's current rigid parameter settings may not adequately accommodate individual fitness levels and exercise habits, despite the overall effectiveness of the strategy.

Considering the findings and limitations of this study, we propose targeted design recommendations for goal-setting features. The design should focus on the SMART goal framework (Specific, Measurable, Achievable, Relevant, Time-bound) to effectively operationalize goal-setting theory. To accommodate diverse fitness levels, the system should afford users flexibility in customizing core parameters (e.g., goal duration and criteria). Furthermore, developing and optimizing an automated goal adjustment model helps sustain exercise challenges appropriate for individual capacities while mitigating user frustration.

5.2 Personal awareness

Personal awareness, which encompasses performance feedback and exercise history, primarily facilitated system use continuation but had a relatively weaker impact on exercise motivation. These findings indicate that such features may enhance user acceptance rather than directly drive exercise engagement, which aligns with prior studies demonstrating that activity tracking improved user retention yet fails to ensure immediate exercise motivation or increased activity [35,36]. Furthermore, goal progress review exhibited weaker correlations with exercise motivation compared to performance feedback and exercise history. This may stem from participants' tendency to prioritize tracking controllable behaviors (e.g., exercise duration and intensity) over slow-changing physiological outcomes (e.g., weight changes and caloric expenditure). Focusing on controllable actions enables individuals to experience a sense of progress and control, which fosters the development of autonomous motivation and thereby increases the likelihood of exercise adherence [37].

Qualitative analysis of personal awareness further revealed insights into its limited motivational impact. First, its motivational effect was attenuated by participants' perceived suboptimal trustworthiness of measurement data, since inaccurate data undermines user trust in persuasive systems [38]. Second, participants reported deficiencies in the personal awareness features, with demands for more comprehensive and flexible operations such as an exercise pause function to accommodate real-world interruptions during physical activity. Third, participants noted that the unclear visual display of goal progress in the exercise calendar hindered their ability to quickly interpret exercise achievements.

Drawing on the findings, we propose design recommendations to optimize personal awareness features. First, it is critical to refine wearable tracking algorithms and calibrate them for common physical activities, thereby reducing discrepancies between measured and actual metrics to enhance user trust in the system. Second, the features should prioritize delivering feedback on controllable behaviors by highlighting real-time metrics, while keeping slow-changing physiological data easily accessible. Third, the system should provide more comprehensive and flexible operational support and offer greater customization of interaction preferences, to enhance the usability and user acceptance of personal awareness features. Finally, intuitive visualization approaches could be adopted to present goal progress, thereby reducing users' difficulties in comprehending the symbolic meaning of elements such as achievement badges and completion trophies. Specific measures include adopting clear, consistent designs to distinguish completed and unmet goals, and incorporating interactive tooltips to explain progress metrics instantly.

5.3 Social influence

Social influence via workout companion and exercise ranking features positively influenced system use intention, potentially driven by peer effects in exercise behaviors which have been demonstrated to be both statistically and socially significant [39]. However, users exhibit heterogeneous preferences for social features in the context of physical activity, meaning that social competition presents both diversity and potential risks [40,41]. Limited evidence indicates that performance rankings have a significant impact on specific exerciser groups [42]. Additionally, the study's adopted ranking criterion (i.e., calories burned) correlated positively with both exercise motivation and system use intention.

Based on the dual findings that social companion and competitive features drive motivation and that qualitative analysis uncovered usability gaps in ranking display and social interaction design, we propose targeted design recommendations for social influence features. First, to enhance the persuasiveness and usability of ranking functions, the system should prominently highlight users' personal ranking positions and incorporate visualized social comparison information (e.g., “you have outperformed 80% of your friends” or “an additional 0.5 km to overtake the next user”) to stimulate self-evaluation and upward competitive motivation. Second, it should incorporate user-to-user interaction features, such as comments, to build stronger emotional connections and facilitate experience sharing. This approach addresses the low engagement associated with one-way social interactions reported by participants. Third, competitive formats should be diversified—for example, by combining individual rankings with team competitions—to accommodate different social motivation preferences. Fourth, the system can maintain calories burned as the core ranking metric while offering optional, customizable ranking criteria (e.g., step count, exercise duration) for those who prioritize non-calorie goals.

5.4 Reinforcement

Positive emotions resulting from receiving rewards had a significant impact on both exercise motivation and system use intention, whereas expectations of future rewards had a weaker influence on sustained use. This suggests that immediate satisfaction from rewards may be more motivating than the anticipation of future rewards. These results are generally consistent with a previous study indicating that immediate rewards can enhance short-term engagement, positivity, and a sense of achievement in physical activity [43]. In addition, qualitative feedback indicated that participants desired clearer visual distinctions in reward representations, specifically requesting for distinct icons for top-ranking users so their achievements would stand out from those of other participants.

Given the dual findings that immediate rewards are more effective for motivation and participants' desire for more distinct reward presentation in qualitative feedback,

we propose targeted design recommendations for reinforcement features. First, the system should focus on immediate, tangible rewards (e.g., issuing digital badges or certificates upon goal completion) and enhance the reward presentation to improve distinction—such as designing tiered reward visuals (e.g., gold/silver/bronze badge variants corresponding to different achievement levels). Second, the system can diversify reward forms by recognizing incremental progress (e.g., rewarding 50% or 75% goal completion) in addition to full goal completion, thereby expanding the motivational reach to users with different performance levels.

5.5 Suggestion and reminder

Fitness and weight management advice was positively correlated with both exercise motivation and continued system use, which is largely consistent with previous research regarding personalized guidance. Multiple studies have shown that computer-tailored or personalized physical activity guidance modestly improves adherence compared with generic advice or no intervention, and that deeply personalized recommendations further enhance physical activity outcomes and improve retention; however, these effects are not universal and are often limited to the short term [44-46].

Regarding exercise reminders, although participants were somewhat open to keeping this feature, it showed no significant correlation with exercise motivation. This discrepancy may be attributed to the one-size-fits-all design of the feature—qualitative analysis further confirmed this, as participants desired reminders better tailored to their personal routines and preferences. This is consistent with previous research indicating that persuasive strategies yield inconsistent effects across individuals; therefore, persuasive interventions should be adapted to fit users and their specific contexts [47].

Based on the dual findings that personalized recommendations drive motivation and system retention and that inflexible reminders cause user annoyance, we put forward targeted design recommendations for the suggestion and reminder strategy. First, designers should provide deeply tailored exercise and weight recommendations that fit users' profiles (e.g., fitness levels, goals, and preferences), while guided by authoritative health guidelines to enhance credibility. Additionally, a customizable reminder system should be implemented, allowing users to control key reminder parameters (e.g. timings/frequencies, formats, trigger conditions, and content) to fit their diverse needs. For example, users could set active time windows to avoid schedule conflicts, select notification formats (e.g., push notifications or voice reminders) that match their usage habits, trigger reminders according to context-specific conditions (e.g., extended periods of inactivity), and customize reminder content (e.g., supportive messages or targeted exercise suggestions).

5.6 Enjoyment interaction

The inclusion of exercise music positively influenced both exercise motivation and sustained system use. This aligns with prior research demonstrating that music listening during exercise promotes physical activity engagement by enhancing positive emotional responses, improving physical performance, reducing perceived exertion, and improving physiological efficiency [48-51]. However, findings regarding the efficacy of exercise music remain inconsistent, which may stem from variations in music selection and individual preferences [48]. Therefore, to sustain long-term system use, the effects of non-music factors (e.g., usable interfaces, functional fit, and moderate personalization) might also be considered; this is supported by qualitative feedback from participants in our study participants, who noted that music alone was insufficient to maintain long-term engagement and expressed demands for more flexible music control and personalized music options.

Drawing on the findings and limitations outlined above, we propose targeted design recommendations for exercise-music interactions. First, the feature could expand music sources and enhance control functionality (e.g., supporting local music playback, track selection and playlist customization). Second, it should incorporate personalized music recommendations (e.g., generating playlists based on user's music preferences and activity types). Third, it could integrate exercise-music synchronization functionality, such as aligning music tempo with exercise intensity or adjusting music based on goals and step frequency. This would leverage the effects of rhythmic entrainment to further reduce perceived exertion and enhance exercise efficiency [49].

6. Conclusion

The integration of persuasive technology into computing contexts can promote physical activity and help individuals incorporate exercise habits into their daily lives. In this study, six categories of persuasive strategies were identified: goal setting, personal awareness, social influence, reinforcement, suggestion and reminder, and enjoyment interaction, implemented through a three-module wearable system. The wearable sensing strap integrated multi-channel ECG and a tri-axial accelerometer to enable acquisition of cardiac and activity data. The terminal application featured local processing capabilities for signal parsing, metric calculation, and dynamic feedback. A remote data server is responsible for the storage and management of user data. To examine the impact of these strategies on the system's persuasive efficacy, a user study was conducted; results demonstrated that the persuasive design exhibits positive potential to motivate physical activity. Specifically, goal setting, social influence, and reinforcement significantly enhanced physical activity motivation, whereas personal awareness, suggestion and reminder, and enjoyment interaction failed to reach statistical significance. Furthermore, participants' intention to continuously use the system was significantly

positively correlated with all six persuasive strategies. Based on the user study findings, the design limitations of the six persuasive strategies were discussed, and targeted improvement directions were proposed accordingly. These findings inform user-centered wearable design for physical activity promotion and provide a validated framework for integrating persuasive design into such systems.

This study has certain limitations, primarily the small sample size and short trial duration, which compromise the generalizability of the research conclusions. Future research should optimize the wearable system based on the proposed improvement directions for the persuasive strategies. Additionally, expanding the sample size and diversifying participant demographics while extending the trial period will enable a more comprehensive evaluation of the system's long-term effectiveness and the impact of individual differences.

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Ethical approval

This study was conducted in accordance with the Declaration of Helsinki and its subsequent amendments. The research protocol was reviewed and approved by the Academic Committee of the Information Engineering School at Liaodong University (approval date: 02 September 2025).

Consent to participate

All participants provided written informed consent and voluntarily participated in the study.

References

- [1] Fletcher GF, Landolfo C, Niebauer J, Ozemek C, Arena R, Lavie CJ. Promoting Physical Activity and Exercise: JACC Health Promotion Series. *Journal of the American College of Cardiology*. 2018 Oct;72(14):1622-1639.
- [2] Carson V, Hunter S, Kuzik N, Gray CE, Poitras VJ, Chaput JP, et al. Systematic Review of Sedentary Behaviour and Health Indicators in School-Aged Children and Youth: An Update. *Applied Physiology Nutrition and Metabolism*. 2016 June;41(6):S240-S265.
- [3] World Health Organization. Global Status Report on Physical Activity 2022: Country Profiles. WHO report CC BY-NC-SA 3.0 IGO. 2023 Jan 31 [cited 2024 Apr 26]; Available from: <https://iris.who.int/bitstream/handle/10665/365761/9789240064119-eng.pdf>.
- [4] Maitland J, Sherwood S, Barkhuus L, Anderson I, Hall M, Brown B, et al. Increasing the Awareness of Daily Activity Levels with Pervasive Computing. In: 2006 Pervasive Health Conference and Workshops (PHCW). 2006. p. 1-9.
- [5] Byrne R, Eslambolchilar P. Encouraging an Active Lifestyle with Personal Mobile Devices: Motivational Tools and Techniques. In: Nudge and Influence through Mobile Devices Workshop (Mobile HCI). 2010. p. 3-6.

- [6] Fogg BJ. *Persuasive Technology: Using Computers to Change What We Think and Do*. San Francisco: Morgan Kaufmann Publisher; 2002.
- [7] Aldenaini N, Alqahtani F, Orji R, Sampalli S. Trends in Persuasive Technologies for Physical Activity and Sedentary Behavior: A Systematic Review. *Frontiers in Artificial Intelligence*. 2020 Apr;3:3-7.
- [8] Yuasa T, Harada F, Shimakawa H. Proposal to Improve Exercise Using the Fogg Behavior Model. In: 2022 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), 2022. p. 1-4.
- [9] Jang SB, Kim M. Digital Fitness Revolution: User Perspectives on Fitbit's Role in Health Management. *Behavioral Sciences*. 2025 Feb;15(2):231.
- [10] Ho MH, Peng CY, Liao Y, Yen HY. Efficacy of a Wearable Activity Tracker With Step-by-Step Goal-Setting on Older Adults' Physical Activity and Sarcopenia Indicators: Clustered Trial. *Journal of Medical Internet Research*. 2024 Nov;26:e60183.
- [11] Compennolle S, DeSmet A, Poppe L, Crombez G, De Bourdeaudhuij I, Cardon G, et al. Effectiveness of interventions using self-monitoring to reduce sedentary behavior in adults: a systematic review and meta-analysis. *The International Journal of Behavioral Nutrition and Physical Activity*. 2019 Aug;16(1):63.
- [12] Hydari MZ, Adjerid I, Striegel A. Health Wearables, Gamification, and Healthful Activity. *Management science*. 2022 Dec;69(7):3920-3938.
- [13] Chang W, Huang Y, Kim D. The influence of gamification features in wearable fitness devices on perceived value, device loyalty, and exercise continuance intention: the moderating role of personal innovativeness. *Humanities and Social Sciences Communications*. 2026 Feb;13:316.
- [14] Lawi A, Faizah A, Susanti, Toto G, Suadun J, Gulo FE. Integrating Mobile Apps and Wearables for Health Behavior Change: A Systematic Review. *Engineering, Technology & Applied Science Research*. 2026 Apr;16(2):34581-34590.
- [15] Yao J, Song D, Xiao T, Zhao J. Smartwatch-Based Tailored Gamification and User Modeling for Motivating Physical Exercise: Experimental Study With the Maximum Difference Scaling Segmentation Method. *JMIR Serious Games*. 2025 Apr;13:e66793.
- [16] Oinas-Kukkonen H, Harjumaa M. Persuasive Systems Design: Key Issues, Process Model, and System Features. *Communications of the Association for Information Systems*. 2009 Mar;24(1):485-500.
- [17] Hartono Y, Murniati MP. Goal Setting Theory: The Effect of Incentive Moderation on Individual Performance. *Research In Management and Accounting*. 2020 Dec;3(2):95-106.
- [18] Locke EA, Latham GP. Building a Practically Useful Theory of Goal Setting and Task Motivation: A 35-Year Odyssey. *American Psychologist*. 2002 Oct;57(9):705-717.
- [19] Epton T, Currie S, Armitage CJ. Unique Effects of Setting Goals on Behavior Change: Systematic Review and Meta-Analysis. *Journal of Consulting and Clinical Psychology*. 2017 Dec;85(12):1182-1198.
- [20] Ward P. Goal setting and performance feedback. In: *Behavioral Sport Psychology: Evidence-Based Approaches to Performance Enhancement*. New York: Springer; 2011. p. 99-112.
- [21] Gardiner CK, Bryan AD. Randomized Controlled Trials of Self-Monitoring Interventions with or without Incentives for Diet and Exercise among Individuals with Overweight or Obesity: Psychological and Behavioural Effects. *British Journal of Health Psychology*. 2021 Nov;26(4):1114-1134.
- [22] Consolvo S, McDonald DW, Landay JA. Theory-Driven Design Strategies for Technologies That Support Behavior Change in Everyday Life. In: *the SIGCHI Conference on Human Factors in Computing Systems (CHI'09)*. 2009. p. 405-414.
- [23] Sun H, Cai Y, Yan J, Yu X, Cao S, Zhang Y. Influential Mechanism of Social Media in Promoting Adolescents' Sports Behavior—A Study Based on Mixed Method. *Journal of Chengdu Sport University*. 2024 July;50(5):109-120.
- [24] Mema E, Spain ES, Martin CK, Hill JO, Sayer RD, McInvald HD, et al. Social Influences on Physical Activity for Establishing Criteria Leading to Exercise Persistence. *PLOS One*. 2022 Oct;17(10):e0274259.
- [25] Orji R, Alsaity A, Chan G. Towards Understanding the Mechanism Through Which Reward and Punishment Motivate or Demotivate Behaviours. *Behaviour & Information Technology*. 2024;43(6):1042-1066.
- [26] Andrew A, Borriello G, Fogarty J. Toward a Systematic Understanding of Suggestion Tactics in Persuasive Technologies. In: *the 2nd International Conference on Persuasive Technology (PERSUASIVE 2007)*. 2007. p. 259-270.
- [27] Liu N, Yin J, Tan SSL, Ngiam KY, Teo HH. Mobile Health Applications for Older Adults: A Systematic Review of Interface and Persuasive Feature Design. *Journal of the American Medical Informatics Association*. 2021 Nov;28(11):2483-2501.
- [28] World Health Organization. Regional Office for the Western Pacific. *The Asia-Pacific Perspective: Redefining Obesity and Its Treatment*. Health Communications Australia, Sydney. 2000 Feb [cited 2026 Mar 20]; Available from: <http://iris.wpro.who.int/handle/10665.1/5379>.
- [29] Oliver N, Flores-Mangas F, De Oliveira R. Towards Wearable Physiological Monitoring on A Mobile Phone. In: *Mobile Health Solutions for Biomedical Applications*. IGI Global; 2009. p. 208-243.
- [30] Lu L, Tao M, Gao J, Gao M, Zhu H, He X. The Difference of Affect Improvement Effect of Music Intervention in Aerobic Exercise at Different Time Periods. *Frontiers in Physiology*. 2024 Apr;15:1341351.
- [31] Nahum-Shani I, Hekler EB, Spruijt-Metz D. Building Health Behavior Models to Guide the Development of Just-In-Time Adaptive Interventions: A Pragmatic Framework. *Health Psychology*. 2015 Dec;34(S):1209-1219.
- [32] Sutton RS, Barto AG. *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge: The MIT Press; 2018.
- [33] Garstang KR, Jackman PC, Healy LC, Cooper SB, Magistro D. What Effect Do Goal Setting Interventions Have on Physical Activity and Psychological Outcomes in Insufficiently Active Adults? A Systematic Review and Meta-Analysis. *Journal of Physical Activity Health*. 2024 Apr;21(6):541-553.
- [34] Booth L, Jongenelis M, Hasking P, Hastings G, Pettigrew S. Promoting Achievable Goals to Increase Physical Activity. *The European Journal of Public Health*. 2023 Oct;33(Suppl 2):ckad160.529.
- [35] Beckett D, Curtis R, Szeto K, Maher C. Changing User Experience of Wearable Activity Monitors Over 7 Years: Repeat Cross-Sectional Survey Study. *Journal of Medical Internet Research*. 2025 Feb;27:e56251.
- [36] Utesch T, Piesch L, Busch L, Strauss B, Geukes K. Self-Tracking of Daily Physical Activity Using a Fitness Tracker and The Effect of the 10,000 Steps Goal: A 6-Week

- Randomized Controlled Parallel Group Trial. *German Journal Exercise and Sport Research*. 2022 May;52(2):300-309.
- [37] Viveiros B, Jacinto M, Antunes R, Matos R, Amaro N, Cid L, et al. Application of the Hierarchical Model of Intrinsic and Extrinsic Motivation in The Context of Exercise: A Systematic Review. *Frontiers in Psychology*. 2025 Feb;16:1512270.
- [38] Attig C, Franke T. Abandonment of Personal Quantification: A Review and Empirical Study Investigating Reasons for Wearable Activity Tracking Attrition. *Computers in Human Behavior*. 2020 Jan;102:223-237.
- [39] Aral S, Nicolaides C. Exercise Contagion in A Global Social Network. *Nature Communications*. 2017 Apr;8(1):14753.
- [40] Tong H, Laranjo L. The Use of Social Features in Mobile Health Interventions to Promote Physical Activity: A Systematic Review. *NPJ Digital Medicine*. 2018 Sep;1(1):43.
- [41] Young F, Alexandrovsky D, Wurhofer D, Krah EM, Smeddinck JD. Shared Achievements: Exploring the Design of Gameful Collaborative Elements and Fostering Social Relatedness Through Team Effort Contributions in a Social Physical Activity Application. *Studies in Health Technology and Informatics*. 2025;324:7-9.
- [42] Yang Y, Goh K, Teo H, Tan S. Compete with Me? The Impact of Online Gamified Competition on Exercise Behavior. *Journal of the Association for Information Systems*. 2023;24(3):912-935.
- [43] Ha Y, Karyda M, Lucero A. Exploring Virtual Rewards in Real Life: A Gimmick or a Motivational Tool for Promoting Physical Activity?. In: the 2020 ACM Designing Interactive Systems Conference (DIS'20). 2020. p. 1847-1858.
- [44] Broekhuizen K, Kroeze W, Van Poppel M, Oenema A, Brug J. A Systematic Review of Randomized Controlled Trials on the Effectiveness of Computer-Tailored Physical Activity and Dietary Behavior Promotion Programs: an Update. *Annals of Behavioral Medicine*. 2012 Oct;44(2):259-286.
- [45] Ikegaya M, Foo J, Murata T, Oshima K, Kim J. Using Personalized Intervention Criteria in a Mobile Just-in-Time Adaptive Intervention for Increasing Physical Activity in University Students: Pilot Study. *JMIR Human Factors*. 2025 May;12:e66750.
- [46] Coppens I, De Pessemier T, Martens L. Exploring the Added Effect of Three Recommender System Techniques in Mobile Health Interventions for Physical Activity: A Longitudinal Randomized Controlled Trial. *User Modeling and User-Adapted Interaction*. 2024 July;34(5):1835-1890.
- [47] Alsiaity A, Oyeboode O, Vassileva J, Orji R. Personalized Persuasive Technologies in Health and Wellness: From Theory to Practice. In: *A Human-Centered Perspective of Intelligent Personalized Environments and Systems*. Cham: Springer; 2024. p. 261-292.
- [48] Ballmann CG. The Influence of Music Preference on Exercise Responses and Performance: A Review. *Journal of Functional Morphology and Kinesiology*. 2021 Apr;6(2):33.
- [49] Park KS, Williams DM, Etnier JL. Exploring the Use of Music to Promote Physical Activity: From the Viewpoint of Psychological Hedonism. *Frontiers in Psychology*. 2023 Jan;14:1021825.
- [50] Terry PC, Karageorghis CI, Curran ML, Martin OV, Parsons-Smith RL. Effects of Music in Exercise and Sport: A Meta-Analytic Review. *Psychological Bulletin*. 2020;146(2):91-117.
- [51] Wang J. Psychological Effects of Music on Physical Exercise Performance. *Journal of Neonatal Surgery*. 2025 Mar;14(10S):437-445.