

Design of a Personalized Persuasive System Based on Estimated Psychological Traits for Promoting Physical Activity and Experimental Evaluation

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Abstract

Promoting and habituating health behaviors, such as physical activity, to extend healthy lifespans is a critical societal issue. To address this, research and development are advancing in mobile health (mHealth) applications to support sustained physical activity through personalized interventions tailored to users' psychological traits. However, conventional methods rely on pre-intervention questionnaires, which impose significant constraints such as response burden and implementation costs. In this study, we designed and implemented a novel persuasive system that overcomes these challenges by automatically estimating psychological traits from users' application operation logs, thereby providing personalized interventions. Furthermore, we integrated reinforcement learning (RL) for dynamic intervention selection, using post-intervention behaviors (physical activity implementation rate, perceived impression of intervention content, and application operation frequency) as rewards. We also utilized a large language model (LLM) to deliver interventions accompanied by highly personalized messages. An experiment in a real-world environment was conducted with 396 participants to evaluate intervention selection strategies (Random, Static Personalization, and Dynamic Personalization using RL). As a result, Dynamic Personalization (DP) achieved an implementation rate 10.4% higher than the Random group and 6.3% higher than the Static Personalization (SP) group and maintained a high physical activity implementation rate of approximately 50% even after six weeks. This study presents results from a large-scale validation experiment in a real-world environment, which aimed to support sustained physical activity, by integrating psychological trait estimation from application logs, RL for dynamic intervention selection, and LLM-based message generation. This work thus provides evidence for the effectiveness of questionnaire-free personalized interventions.

Keywords

Psychological Traits, Personalized Intervention, Reinforcement Learning

1. Introduction

Promoting and habituating health behaviors, such as physical activity, to extend healthy lifespans is a critical societal issue. To address this, mobile health (mHealth) applications are increasingly being used to intervene with individuals, and services that promote sustained physical activity (among other health behaviors) are becoming widespread. However, in such unmediated applications, the number of active users tends to decrease exponentially over the service implementation period. This phenomenon is known as “The Law of Attrition” [1]. Consequently, in recent years, research and development to support sustained physical activity have been ongoing through personalized interventions tailored to users' individual characteristics.

This study aims to design and implement a personalized persuasive system. This system utilizes specific post-intervention user behaviors as rewards to enable reinforcement learning (RL) for intervention selection, based on multiple psychological traits estimated from users' application operation logs, with the objective of promoting sustained physical activity and habituation. We then evaluate the effectiveness of this system in real-world settings.

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2. Theoretical Background

“MyBehavior” [2] is a pioneering mHealth study that implemented personalized interventions. This system generates individualized interventions that encourage users to continue, avoid, or fine-tune existing behaviors by analyzing their physical activity (e.g., walking, running, gym), current location information, and dietary intake. It leverages past behavior and location, but does not control interventions by psychological traits.

Alqahtani et al. [3] proposed a prior study that optimizes interventions based on individual psychological traits. Their research models the relationship between individual traits and intervention types using Partial Least Squares Structural Equation Modeling (PLS-SEM). Similarly, Shiraishi et al. [4] conducted an internet survey with over 1000 participants to collect data on preferred intervention types and their relationship with psychological traits, which they then modeled using PLS-SEM. Subsequently, this model was utilized in a real-world intervention experiment to confirm its effectiveness in improving implementation rates.

The study of Shiraishi et al. [4] employs nine psychological traits. First, *Big Five* [5] is used as personality traits reflecting an individual's stable character. To reduce participant burden, the Ten Item Personality Inventory [6], consisting of only ten questions, was adopted. Additionally, drawing on BJ Fogg's *B=MAP model* [7] and Bandura's *Social Cognitive Theory* [8], we used two psychological traits as sources of behavioral motivation: *General Self-Efficacy Scale* [9], representing the belief that one can plan and execute actions necessary to achieve goals, and *Challenge Success Need* [10], representing the willingness to tackle difficult tasks. Furthermore, *Promotion-Prevention Focus Scale* [11] is used as a characteristic related to the tendency to control one's own behavior, such as whether one prefers gains or dislikes losses. However, obtaining responses to the 38-item pre-intervention questionnaire for these nine psychological traits would require imposing users to answer a large number of questions, which would be a significant burden.

To address this issue, Yamamoto et al. [12] developed a technology to estimate psychological traits from users' application operation logs, confirming its ability to predict multiple psychological traits such as Big Five and Self-Efficacy. Furthermore, research on personalized interventions using RL is also progressing. For example, Yom-Tov et al. [13] developed a mobile application that uses RL, with physical activity performed after intervention message delivery as a reward, to select and send SMS messages that are highly likely to increase physical activity in diabetic patients.

In designing systems that promote behavioral change, the principles of Persuasive System Design (PSD) are widely employed. The PSD model proposed by Oinas-Kukkonen et al. [14] provides a comprehensive framework to support the design of information systems aimed at changing user attitudes and behaviors. This model categorizes persuasive functions into areas such as “Primary Task Support”, “Dialogue Support”, “Social Support”, and “Trustworthiness Support”, systematizing specific persuasive principles corresponding to each.

In this study, we integrated psychological trait estimation from application operation logs [12] into a persuasive system, enabling questionnaire-free, trait-based personalization. To enhance intervention effectiveness, we incorporated RL-based intervention selection using post-intervention behaviors as rewards, including implementation rate, user impressions (e.g., increased/decreased motivation), and application interaction frequency. We also implemented PSD-based features and intervention types to strengthen behavior change effects.

The proposed system dynamically combines psychological trait estimation, RL-based intervention selection, and LLM-driven message generation within a unified persuasive framework.

We conducted a 6-week in-the-wild experiment with 396 participants to promote physical activity and habit formation. This research presents the first system that automatically estimates psychological traits from application operation logs and reports results from real-world use.

3. Method

3.1. System

Figure 1 illustrates the design of our personalized persuasive system for physical activity habituation. When registering with the system, users answer several questions, as shown in Figure 2, to determine their current exercise habit stage, ranging from 0 to 6. After setting an exercise plan, the system becomes available for use.

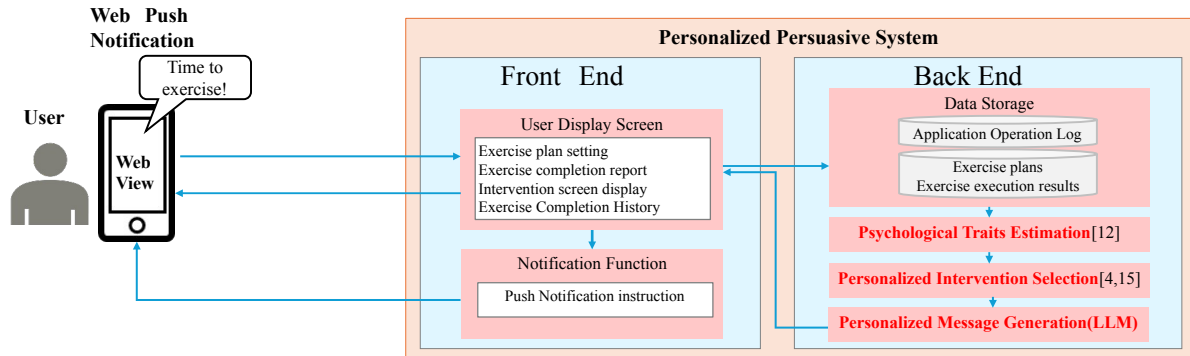


Figure 1: Design for a personalized persuasive system.

Exercise Plan Setting and Completion Report: Users select and establish suitable exercise plans (what to do and when) from a list of options. At this point, exercise plans are presented as a list tailored to the user's exercise habit stage. This prevents users with no exercise habits whatsoever (Stage 0) from being presented with high-load tasks, such as a 30-minute run. After completing an exercise, users can tap the reminder notification, which brings up the system's completion report screen for registration.

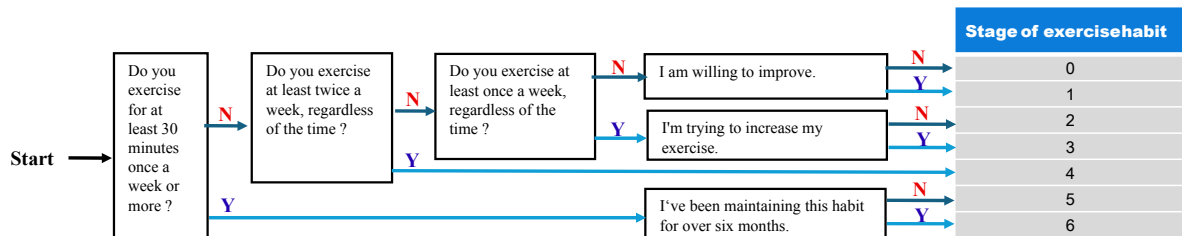


Figure 2: Exercise Habit Stage Determination Flowchart.

Plan Completion History: Users can view their exercise plan completion history from the application menu. Figure 3 shows an example of the Plan Completion History. Users can set up to three exercise plans per day. If all plans are completed, the corresponding day is marked yellow; if some plans are completed but not all, it is marked blue; and if no plans are completed despite being set, it is marked red. Days with no plans set are marked gray.

Reminder: Users set the time for reminder notifications when configuring their exercise plans. When the set time arrives, users receive notifications on their smartphones or work-issued PCs through browser Web Push notifications or work email addresses. Users were allowed to choose either Web Push notifications or email notifications, but disabling both options was not permitted. That is, users were not allowed to disable all notifications.

Personalized Intervention: The system sends an email containing a URL to the user during weekday lunch breaks when an exercise plan is set. When users open the URL, the system

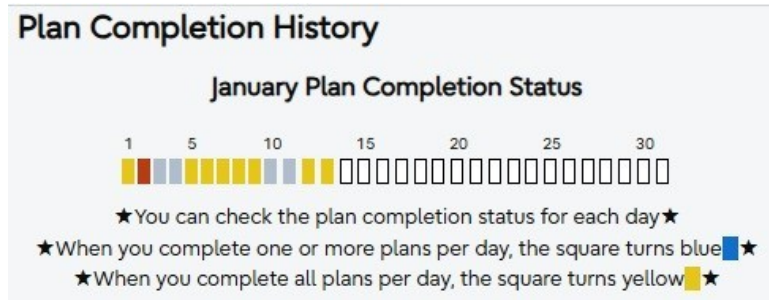


Figure 3: Plan Completion History.

presents an intervention screen that includes AI-generated messages composed of text and images. Details of the intervention control are described in the following section.

3.2. Intervention Design

Unlike conventional questionnaire-based approaches, our system enables questionnaire-free personalized intervention by estimating psychological traits directly from application operation logs.

Psychological Traits Estimation [12]: Four psychological trait categories are estimated from weekly aggregates of operation logs, including plan completion, screen views, and plan-setting behavior. Trait estimation is performed after the first 7 days of usage and updated weekly thereafter.

To define the intervention space used for personalization, we defined six intervention types based on prior work [4], as summarized in Table Table 1.

Table 1: Intervention types.

Name	Details
Contribution	Notification of situations where you are leading the group.
Pressure	Notification of situations where you are falling behind within the group.
Superiority	Notification that your performance is above the group average.
Inferiority	Notification that your performance is below the group average.
Gain	Notification of the positive effects of engaging in physical activity.
Loss	Notification of the negative effects of neglecting physical activity.

Personalized Intervention Selection: We designed a personalized intervention framework using these six intervention types (Table Table 1, Figure Figure 4) and compared three intervention selection strategies:

1. **Random:** Uniformly samples one of the six types each day.
2. **Static Personalization (SP):** This strategy uses estimated psychological traits to calculate the preference levels for each intervention type via PLS-SEM modeling, then randomly samples the top three.
3. **Dynamic Personalization (DP):** This strategy follows the RL framework of Shiraishi et al. [15]. The system monitors each user’s behavioral state, defined by recent completion rate, interaction frequency, and weekly trend, and selects one of six intervention types. The RL policy is updated daily based on the previous day’s outcomes, and the updated policy determines the next intervention. The RL rewards combine normalized post intervention signals, prioritizing task completion while incorporating user impressions and interaction frequency as secondary factors.

Cold Start Policy: Because psychological trait estimation requires at least 7 days of application operation log accumulation, all users, regardless of their assigned strategy, received random interventions during the first 7 days.

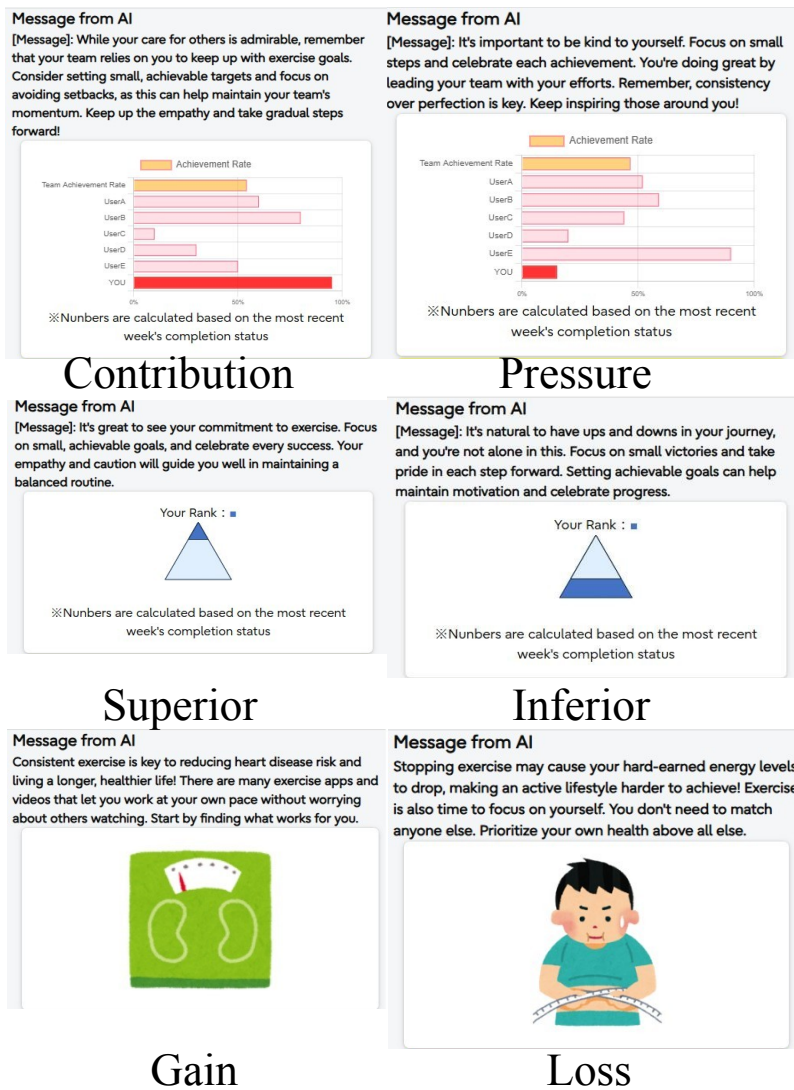


Figure 4: 6 types of Intervention that displayed to application users.

Personalized Message Generation (LLM): To reduce message fatigue from repeated interventions, the system uses an LLM (GPT-4o) to generate a personalized message displayed at the top of the intervention screen (Figure Figure 4). The LLM takes as input the user's estimated psychological traits, recent implementation status, and the selected intervention type, and produces a tailored message for each delivery.

Following Persuasive Systems Design (PSD) [14], Table Table 2 summarizes how the system components map to PSD principles. Users choose habit-stage appropriate exercise plans during setup (Reduction), review their plan completion history in the app (Self-monitoring), and receive scheduled notifications (Reminder). Intervention content is tailored to each user (Personalization).

In addition, the "Superior" and "Inferior" indicators in Figure Figure 4 present relative performance (Social comparison), while "Contribution" and "Pressure" messages promote awareness of team performance (Cooperation).

3.3. Study Setting (in the wild experiment)

To evaluate several intervention selection strategies based on users' psychological traits estimated from application operation logs, we conducted a real-world experiment using the developed system. Participants were recruited from among employees of an ICT company in Asia via recruitment emails. Additionally, participants were allowed to withdraw from the study before its commencement if they did not agree to the handling of personal information or the application's

Table 2: Mapping between system features and Persuasive System Design (PSD) principles.

Category for persuasive system principles	Principles	Features in this persuasive system
Primary task support	Reduction	Users select and set their own exercise plans from diverse options suited to their current stage of exercise habit.
	Personalization	Intervention selection and message generation tailored to psychological traits and plan completion status.
	Self-monitoring	Display plan completion history in the application.
Dialogue support	Reminders	Notifications via email/Web Push at user-set days and times.
Social support	Social comparison	Intervention types of “Superior” and “Inferior” indicate a user’s rank within a group, encouraging social comparison with other users.
	Cooperation	The “Contribution” and “Pressure” intervention types encourage users to be mindful of their own performance within the team, thereby increasing their motivation to cooperate.

terms of use. There were no rewards for participation; instead, participation was requested on a voluntary basis. Consequently, participants had no obligations and were free to cease using the system at any time. Participants were asked to access the system (shown in Figure Figure 1) from their smartphones or work-issued PCs, complete a questionnaire for account creation and exercise habit stage determination (Figure Figure 2), and set up to three exercise plans per day.

3.4. Evaluation

Evaluation used the physical activity implementation rate as the primary outcome, reflecting behavioral change induced by the persuasive system. Participants were assigned to three intervention-selection strategy groups (Table Table 3). To reduce baseline-related differences in implementation rates, pre-experiment exercise habit stages (Figure Figure 2) were balanced across groups.

Analyses included 396 participants who submitted at least two plan completion reports. Because recruitment was voluntary, many users set plans but submitted none or only one completion report; therefore, we restricted analyses to participants who submitted two or more completion reports. The resulting sample size (N=396) was judged sufficiently large relative to those reported in prior reviews of individualized physical activity interventions [16].

The study lasted six weeks. Intervention notifications were sent to work email addresses on weekdays, and implementation rates were aggregated over 34 weekdays (excluding weekends) to highlight differences across strategies. Exercise habit stages (Figure Figure 2) were also assessed post-experiment, and pre/post stage changes were evaluated as an outcome of habit formation.

Table 3: Number of participants in each group.

Group	Assigned participants	Number of participants used in the analysis (registered two or more completion reports)
Random intervention (Random)	228	134
Static personalization (SP)	225	134
Dynamic personalization (DP)	218	128
Total	671	396

4. Experimental Result

4.1. Implementation rates

Figure 5 illustrates the transition of implementation rates for each intervention selection strategy. The vertical axis represents the implementation rates smoothed using a five-day moving average. The gray area denotes the initial period during which all groups received a random selection of intervention. After 6 weeks, the dynamic personalization group (DP), which used RL-based intervention selection, showed a 6.3% higher implementation rate than the static personalization group (SP). Furthermore, DP demonstrated a 10.4% higher implementation rate compared to the random intervention group (Random).

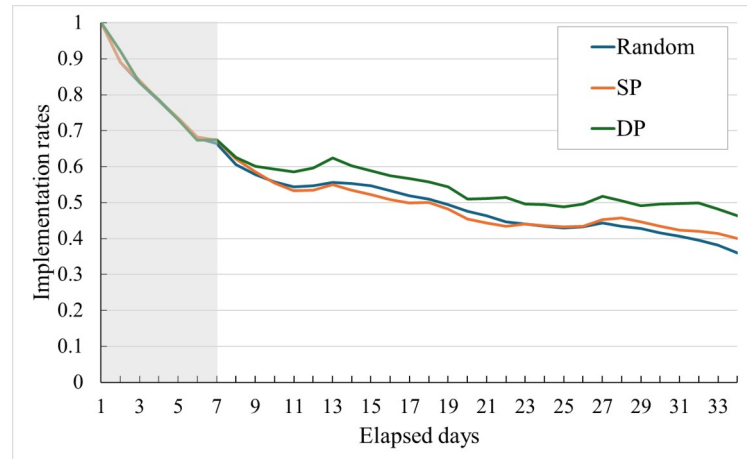


Figure 5: Transition of implementation rates.

For the implementation rate over the 7 days including the final day (days 28–34), participants were categorized as “implementers” (those who registered completion reports for one or more of the exercise plans set for that day) and “non-implementers” (those who did not implement at all). Applying a chi-square test to the implementers and non-implementers categories revealed a significant difference between the DP group and the random group ($df=1$, $\chi^2=17.828$, $p=2.4176e-05$, *Cohen's d*=0.21).

We also confirmed that this persuasive system, using RL-based intervention selection, could maintain an implementation rate of approximately 50% even after 6 weeks. Conversely, a sharp decline in implementation rates from the start of registration was also observed in this experiment.

4.2. Change of exercise habit stage between before/after experiments

From the post-experiment survey, 83% of participants (N=329), we investigated changes in exercise habit stage. Figure 6 illustrates the proportion of participants whose exercise habit stage changed before and after the experiment. Although no significant differences in habit-stage transitions were observed among the three strategies.

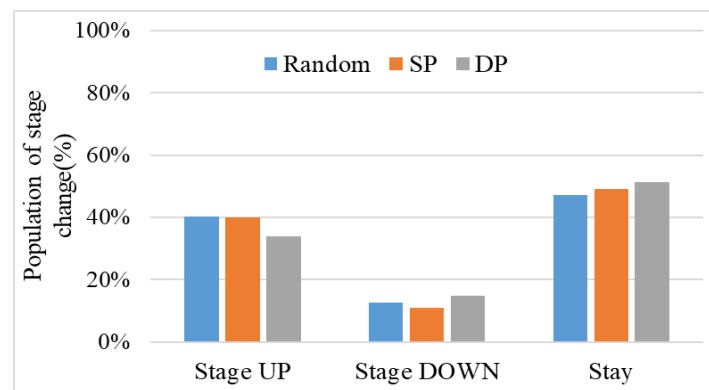


Figure 6: Exercise habit stage changes before and after the experiments.

5. Discussions

In this experiment, the dynamic personalization group (DP) demonstrated a relatively high implementation rate, but a phenomenon where the implementation rate declined sharply from the start of registration was also observed. This aligns with “The Law of Attrition” [1] mentioned in the Introduction. This decline may stem from the *cold start problem* during the first week after registration, where psychological traits could not be estimated. During this period, a temporary random selection of interventions was implemented for all users. Resolving the personalization challenges during this initial period is expected to curb the sharp decline in usage and is identified as a future challenge.

Additionally, dynamically personalized LLM-generated messages are applied across all groups. The intervention type is also used as input for this message generation, and the performance of the intervention type selection influences the content of the LLM-generated messages. Therefore, the individual contributions of the LLM-generated messages and the RL selection logic cannot be analyzed, making this a topic for future consideration.

We also consider the lack of observed changes in exercise habit stages. This is as expected, since a 6-week experimental period is typically insufficient to detect changes in long-term behavioral structures. Importantly, approximately 40% of participants showed an improvement in their habit stage across all strategies, indicating that the system as a whole supported the early development of exercise habits. These results suggest that the short-term behavior change induced by personalized interventions—especially the high completion rates achieved by DP—may contribute to longer-term habit formation when applied over an extended period.

6. Conclusions and Future Work

This study designed and implemented a persuasive system that automatically estimates psychological traits from mHealth application usage logs and delivers personalized interventions based on these estimated traits. This system achieves psychological trait-based personalized interventions without requiring traditional questionnaires.

In a real-world experiment that evaluated three intervention selection strategies, the RL-based intervention selection resulted in an approximate 50% implementation rate after 6 weeks. Furthermore, the use of this persuasive system led to approximately 40% of post-survey respondents reporting an improvement in their exercise habit stage. Future efforts will focus on addressing *cold start problem*—a method for implementing personalized interventions immediately after users begin using the persuasive system.

Acknowledgments

This study was approved by the Institutional Review Board of Hokkaido University (Approval No. R7-14).

Declaration on Generative AI

During the preparation of this work, the authors used Gemini 2.5 Pro in order to: Text Translation, Paraphrase and reword, Grammar and spelling check, peer review simulation, content enhancement. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

References

- [1] Gunther Eysenbach, The law of attrition, Journal of Medical Internet Research, vol.7, no.1 (2005). doi: 10.2196/jmir.7.1.e11
- [2] M. Rabbi, A. Pfammatter, M. Zhang, B. Spring, Automated personalized feedback for physical activity and dietary behavior change with mobile phones: a randomized controlled trial on

- adults, *Journal of Medical Internet Research mhealth and uhealth*, vol.3, iss.2 (2015). doi:10.2196/mhealth.4160
- [3] F. Alqahtani, S. Meier, and R. Orji, Personality-based approach for tailoring persuasive mental health applications, *User Modeling and User-Adapted Interaction*, vol. 32, no. 3, pp. 253–295 (2022). doi: 10.1007/s11257-021-09289-5
- [4] M. Shiraishi, Y. Masuda, T. Yamamoto, S. Hayakawa, T. Kamimura, H. Iizuka and K. Suzuki, Experimental evaluation of personalized intervention based on the PLS-SEM model for physical activity, *IEEE Int. Conf. on System, Man and Cybernetics (SCM2025) on Proceedings*, pp. 1–7. Austria (2025).
- [5] L. R. Goldberg, An alternative ‘description of personality’: The big-five factor structure, *Journal of Personality and social psychology*, vol. 59, no. 6, pp.1216-1229 (1990). doi: 10.1037/0022-3514.59.6.1216
- [6] S. D. Gosling, P. J. Rentfrow and W. B. Swann Jr., A very brief measure of the Big-Five personality domains, *Journal of Research in Personality*, vol. 37, no.6, pp.504-528 (2003). doi: 10.1016/S0092-6566(03)00046-1
- [7] B. J. Fogg, A behavior model for persuasive design, *Proceedings of the 4th international Conference on Persuasive Technology (2009)*. doi: 10.1145/1541948.154199
- [8] A. Bandura, *Social foundations of thought and action: A social cognitive theory*, Prentice Hall (1986).
- [9] A. Miyoshi, Development of the subjective sensation of personality trait Self-Efficacy Scale (SMSGSE), *Japanese Journal of Developmental Psychology*, vol.14, no.2, pp.172-179 (2003) (In Japanese).
- [10] M. Horino, Analysis of the components of achievement motivation, *Japanese Journal of Educational Psychology*, vol.35, no.2, pp.148-154 (1987) (In Japanese).
- [11] P. Lockwood, C.H. Jordan and Z. Kunda, Motivation by positive or negative role models: regulatory focus determines who will best inspire us, *Journal of Personality and Social Psychology*, vol.83, no.4, pp.854-864 (2002). doi: 10.1037//0022-3514.83.4.854
- [12] T. Yamamoto, S. Hayakawa, M. Shiraishi, Y. Masuda, M. Matsuki and T. Kamimura, Psychological traits estimation using generative adversarial networks for personalized intervention, *HCI International 2025 – Late Breaking Papers, CCIS*, vol. 2772, pp. 178–189. Springer, Cham (2026). doi: 10.1007/978-3-032-12767-9_20
- [13] E. Yom-Tov, G. Feraru, M. Kozdoba, S. Mannor, M. Tennenholtz and I. Hochberg, Encouraging physical activity in patients with diabetes: Intervention using a reinforcement learning system, *Journal of Medical Internet Research*, 19(10) (2017). doi: 10.2196/jmir.7994
- [14] H. Oinas-Kukkonen, M. Harjumaa, Persuasive system design: Key issues, process model, and system features, *Communications of the Association for Information Systems*, Vol. 24 (2009). doi: 10.17705/1CAIS.02428
- [15] M. Shiraishi, Y. Masuda, T. Yamamoto, S. Hayakawa, T. Kamimura, H. Iizuka and K. Suzuki, Dynamic personalized interventions using reinforcement learning with theory-based reward function, *Proceedings of the 21st International Conference on Persuasive Technology, Japan (2026)*.
- [16] S. Ghanvatkar, A. Kankanhalli and V. Rajan, User models for personalized physical activity interventions: Scoping review, *Journal of Medical Internet Research mhealth and uhealth*, vol.7, iss.1, e11098 (2019). doi: 10.2196/11098