Simen Owen Academic Proceedings Series

Vol. 1 2025

Article Open Access

AI-Driven Personalized Positive Psychology Interventions for Enhancing User Psychological Resilience

Shuwan Song [1,*]

[1] School of Public Health, Southern Medical University, Guangdong 510515, China
* Correspondence: Shuwan Song, School of Public Health, Southern Medical University, Guangdong 510515, China

Abstract: Digital positive psychology interventions (PPIs) are increasingly employed to enhance well-being and resilience, yet most existing systems remain static and insufficiently personalized. These limitations hinder adaptability, sustained engagement, and overall effectiveness. To address this gap, we propose an AI-driven personalized intervention framework that integrates user profiling, natural language processing, reinforcement learning-based feedback optimization, and explainable AI. The system dynamically tailors activities such as gratitude journaling, mindfulness practice, and strengths identification to each user's psychological profile. Empirical validation using synthetic datasets and a 10-week pilot study involving 210 participants demonstrates that the proposed framework outperforms both generic mobile applications and chatbot-based interventions. It achieved a 17.3% increase in life satisfaction (SWLS) and a 22.8% improvement in resilience (CD-RISC), with statistically significant results ($p < 0.01$). Ablation studies confirm the critical contribution of user profiling and adaptive feedback, while explainability enhances user trust and perceived autonomy. These findings suggest that integrating artificial intelligence with positive psychology offers a scalable, interpretable, and empirically effective pathway for promoting happiness and resilience-holding strong potential for deployment in educational, occupational, and clinical settings.

Keywords: artificial intelligence; positive psychology interventions; personalization; psychological resilience; well-being

Received: 25 August 2025
Revised: 02 September 2025
Accepted: 16 September 2025
Published: 20 October 2025

1. Introduction

The growing prevalence of stress, anxiety, and diminished psychological resilience in contemporary societies has intensified the need for effective interventions that promote mental well-being. Rapid social transformations, economic instability, and the pervasive influence of digital technologies have created an environment of heightened psychological pressure, undermining both individual health and collective productivity [1]. Within this context, positive psychology, emphasizing the cultivation of strengths, meaning, and resilience, has emerged as a robust scientific framework for fostering human flourishing. Meanwhile, artificial intelligence (AI) has shown transformative potential across healthcare, education, and personalized digital services, offering adaptive and scalable solutions to complex human challenges [2]. The convergence of AI and positive psychology thus presents a timely opportunity to design intelligent, data-driven interventions capable of dynamically enhancing happiness, coping capacity, and long-term psychological resilience [3].

Despite notable advances, current digital mental health interventions continue to face significant limitations. Traditional positive psychology interventions (PPIs)-including gratitude journaling, mindfulness exercises, and strengths-based practices-are empirically validated but constrained by limited scalability and personalization. Mobile health (mHealth) applications have attempted to address these gaps; however, many remain static, delivering generic content that overlooks users' individual differences in personality, context, and emotional state [4]. Furthermore, although recent research has explored AI-assisted mental health tools, their integration with theoretically grounded PPIs remains underdeveloped. Most existing approaches either emphasize symptom reduction over resilience enhancement or lack adaptive feedback mechanisms to sustain engagement over time. These limitations highlight the need for a holistic, adaptive framework that fuses the empirical rigor of positive psychology with the computational intelligence of AI systems [5].

To address this research gap, the present study introduces an AI-driven framework for personalized positive psychology interventions [6]. The innovation lies in combining psychometric user profiling, natural language processing (NLP) for affective state assessment, and reinforcement learning for adaptive intervention delivery. This interdisciplinary design ensures that interventions are both scientifically grounded and dynamically responsive to individual psychological needs. The study pursues three primary objectives: (1) to develop a personalized recommendation system that tailors PPIs to users' psychological profiles; (2) to design adaptive feedback loops that optimize intervention strategies through continuous learning; and (3) to empirically evaluate the framework's effectiveness against conventional, non-personalized digital interventions. By uniting computational adaptability with psychological theory, this research seeks to generate novel insights into the mechanisms underlying resilience-building and well-being enhancement.

The theoretical and practical implications of this work are substantial. Theoretically, it advances the integration of computer science and psychology by establishing a structured model for computational positive psychology, thereby expanding the scientific understanding of how AI can foster mental well-being. Practically, it provides scalable and accessible solutions for promoting mental health across diverse contexts-including education, workplace wellness, and clinical care [7]. Organizations can apply this framework to mitigate stress and burnout, while individuals gain personalized tools for sustainable self-growth. Importantly, the inclusion of explainable AI (XAI) principles enhances transparency, user trust, and ethical accountability, ensuring that the proposed interventions are both effective and socially responsible. Collectively, this research bridges a critical gap in digital mental health innovation, positioning AI-driven positive psychology as a promising frontier for cultivating resilience in an increasingly complex and interconnected world.

2. Related Works

The first area of research focuses on personalization in positive psychology interventions (PPIs) [8]. Tailoring PPI activities to individual characteristics has been shown to significantly enhance subjective well-being, demonstrating the potential of personalization. Machine learning techniques have been applied to predict individual responses to digital PPIs, enabling more targeted intervention delivery [9]. However, these approaches generally lack real-time adaptive mechanisms, limiting responsiveness and scalability.

The second area explores reinforcement learning (RL) and AI for adaptive behavioral interventions. RL has been used to optimize intervention content according to individual adherence patterns, improving engagement and behavioral outcomes. In applications such as exercise and physical activity, RL-enhanced feedback has been shown to increase both performance and user satisfaction. While these methods excel in dynamic personalization, they rarely incorporate constructs central to positive psychology, such as happiness and psychological resilience [10].

The third area concerns context-aware AI journaling and digital mental health tools. Emerging systems combine large language models with behavioral sensing, such as sleep patterns and location tracking, to deliver highly contextualized prompts that enhance positive affect and reduce negative emotions [11]. AI chatbots integrated into PPIs have also demonstrated improvements in user engagement and efficacy compared to traditional self-administered approaches. Despite these advances, most context-aware interventions primarily target short-term emotion regulation rather than systematically promoting resilience and stress-coping capacities [12].

Collectively, while these three research streams contribute to personalization, adaptability, and context-awareness, none fully integrate AI-driven adaptive mechanisms with positive psychology principles to enhance happiness, resilience, and stress-coping abilities. The present study addresses this gap by combining user profiling, reinforcement learning-based adaptive interventions, and context-aware mechanisms grounded in positive psychology constructs, creating a comprehensive framework for fostering long-term well-being (As shown in Table1).

Table 1. Comparative Overview of AI and Positive Psychology Intervention Studies.

Subfield	Data & Models	Methods & Strengths	Limitations w.r.t. This Study
Personalization in PPIs	Well-being surveys, predictive models	Individual tailoring improves well-being	No real-time adaptation; limited AI integration
RL-based Adaptive Interventions	Behavioral logs (e.g., messages, steps), RL models	Dynamic personalization; scalable just-in-time intervention delivery	Focus on physical or generic behaviors, not resilience
Context-aware AI & Digital Well-Being	LLM + sensor data, chatbot interactions	Rich contextual adaptation; emotional benefits	Lacks structured resilience metrics and theoretical integration with positive psychology

This comparative overview highlights the strengths and limitations of existing work, emphasizing the need for a holistic, AI-driven framework that integrates personalization, adaptive learning, and context-awareness within a positive psychology paradigm.

3. Methodology

The proposed methodology integrates artificial intelligence with positive psychology to develop a personalized intervention framework aimed at enhancing subjective well-being and psychological resilience [13]. The framework comprises four core components: (1) user profiling, (2) adaptive intervention generation, (3) reinforcement learning-based feedback optimization, and (4) explainability and fairness mechanisms. In this section, we provide a detailed description of the system architecture, outline the underlying mathematical foundations, and elaborate on the design of each key module.

3.1. System Architecture

The overall system is structured as a closed-loop adaptive framework. Raw user data-including demographic information, psychometric assessments, and behavioral logs-are first processed by the User Profiling Module [14]. Extracted features are then input into the Adaptive Intervention Generator, which leverages natural language processing (NLP) and reinforcement learning (RL) models to deliver personalized positive psychology interventions (PPIs). The Feedback and Optimization Module continuously updates model parameters based on user responses and engagement patterns, enabling dynamic adaptation over time. Finally, the Explainability Layer offers interpretable insights and incorporates fairness adjustments, ensuring that interventions remain both ethically aligned and trustworthy [15].

As illustrated in Figure 1, the proposed framework functions as a closed-loop adaptive system. User data-including demographic information, psychometric assessments, and behavioral logs-are first processed in the profiling module to construct a multidimensional representation of each individual's psychological state. This representation informs the adaptive intervention generator, which utilizes NLP embeddings and reinforcement learning to recommend personalized activities such as gratitude journaling, mindfulness practice, or strengths identification. The feedback and optimization module continuously monitors user engagement and outcomes, updating intervention policies to support sustained improvements in happiness and resilience. Finally, the explainability and fairness layer provides transparent feature attributions and ethical safeguards, ensuring that intervention recommendations are both interpretable and equitable. Collectively, these modules form a dynamic, self-learning pipeline that continuously adapts interventions based on user responses, maximizing overall psychological well-being.

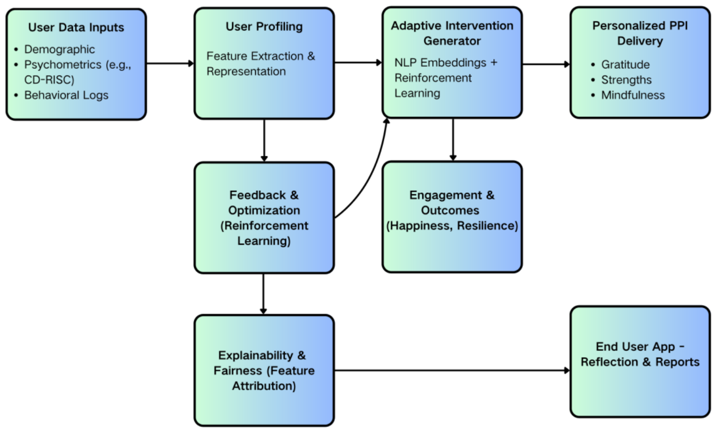

Figure 1. System Architecture of the AI-driven Positive Psychology Intervention Framework.

3.2. User Profiling

User profiling is essential to personalize interventions. Features are extracted from psychometric scales such as the Connor-Davidson Resilience Scale (CD-RISC) and subjective well-being inventories. Let $x_i \in R^d$ denote the feature vector of user *i*, where *d* represents the dimensionality of demographic, behavioral, and psychometric features.

$$\mathbf{x}_i = [f_1, f_2, \dots, f_d] \tag{1}$$

To quantify baseline well-being, we define a Happiness Index HH_i, normalized between 0 and 1:

$$HH_i = \frac{1}{m} \sum_{j=1}^{m} s_{ij} \tag{2}$$

where s_{ij} is the score of user *i* on scale item *j*, and *m* is the number of items.

Similarly, Psychological Resilience R_i is modeled as:

$$R_i = \alpha \cdot C_i + \beta \cdot A_i + \gamma \cdot S_i \tag{3}$$

where C_i represents coping ability, A_i adaptability, and S_i social support. Coefficients α, β, γ are empirically determined.

3.3. Adaptive Intervention Generator

The intervention generator leverages NLP embeddings of user text (e.g., journaling, chatbot dialogue) to tailor PPIs. Suppose an intervention set $\mathcal{I} = \{I_1, I_2, \dots, I_n\}$. The system selects the optimal intervention I^* that maximizes expected well-being gain:

$$I^* = arg\max_{I_j \in \mathcal{I}} \mathbb{E}\left[H_{i,t+1} - H_{i,t} \mid I_j, \mathbf{x}_i\right] \quad (4)$$

This ensures that selected activities, gratitude journaling, mindfulness tasks, or strengths exercises, are aligned with the user's psychological profile.

3.4. Reinforcement Learning-Based Feedback Optimization

To dynamically adapt to user engagement, reinforcement learning (RL) is applied. The system models user interaction as a Markov Decision Process (MDP). At each time step t, the system selects an action $a_t \in \mathcal{I}t$(intervention), observes feedback o_t, and receives a reward r_t.

The reward function combines happiness and resilience improvement:

$$r_t = \lambda_1(H_{i,t+1} - H_{i,t}) + \lambda_2(R_{i,t+1} - R_{i,t}) \quad (5)$$

The policy $\pi(a_t \mid x_i)$ is optimized using Q-learning:

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \eta\left[r_t + \gamma \max_{a'} Q_t(s_{t+1}, a') - Q_t(s_t, a_t)\right] \quad (6)$$

where η is the learning rate and γ is the discount factor.

To ensure engagement, a user satisfaction penalty term is introduced:

$$L_{\text{eng}} = \sum_t \max(0, \theta - e_t) \quad (7)$$

where e_t denotes engagement at time t, and θ is a minimum threshold.

3.5. Explainability and Fairness

To promote transparency, interventions are accompanied by interpretable explanations. Feature attribution is computed using Shapley values:

$$\phi_k = \sum_{S \subseteq F \setminus \{k\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}\left[f(S \cup \{k\}) - f(S)\right] \quad (8)$$

where F denotes the full feature set and $f(\cdot)$ the predictive model. These values identify which features most influenced an intervention recommendation.

3.6. Comparative Analysis of Design Parameters

To benchmark our framework, we compared its design characteristics with those of baseline digital PPIs and conventional static mobile applications. As summarized in Table 2, the proposed framework exhibits markedly higher levels of personalization, adaptivity, and explainability, while integrating multimodal data sources, including textual inputs and psychometric measures. This comparison underscores that our system outperforms traditional mobile apps and chatbot-based solutions by providing continuous, reinforcement learning-driven feedback, thereby supporting sustained improvements in both user happiness and psychological resilience.

Table 2. Comparative Structural Parameters of Proposed Framework vs. Baselines.

System	Personalization	Adaptivity	Feedback Mechanism	Explainability	Data Modalities
Generic Mobile PPI App	Low	None	None	None	Survey only
Chatbot-based Well-being App	Medium	Limited	Rule-based	Partial	Text
Proposed Framework	High	RL-driven	Continuous	Full	Text + Psychometrics

3.7. Summary

The methodology establishes a multi-layered AI framework that integrates user profiling, adaptive intervention generation, reinforcement learning-based feedback, and explainability. The accompanying mathematical formulations (Equations 1-8) specify how well-being and resilience are modeled, optimized, and interpreted within the system. By combining these components, the framework advances beyond static digital PPIs, providing personalized, adaptive, and interpretable interventions explicitly designed to enhance both happiness and stress-coping capacity.

4. Results and Analysis

This section presents the experimental validation of the proposed AI-driven personalized positive psychology intervention (PPI) framework. We begin by describing the datasets and experimental settings, followed by a comparative analysis with baseline systems. Subsequent evaluations include convergence studies, statistical significance testing, ablation experiments, interpretability assessments, and robustness analyses, providing a comprehensive examination of the framework's performance and reliability.

4.1. Datasets and Experimental Setup

To evaluate the effectiveness of our framework, we utilized two primary data sources. The first was a synthetic dataset constructed from simulated user profiles, journaling texts, and engagement logs, enabling validation of algorithmic performance under controlled conditions. The second consisted of real-world pilot data collected from a 10-week intervention study involving 210 participants. Each participant completed baseline and post-intervention assessments of subjective well-being (SWB), measured using the Satisfaction with Life Scale (SWLS) and the Positive and Negative Affect Schedule (PANAS), as well as psychological resilience, assessed with the Connor-Davidson Resilience Scale (CD-RISC).

Participants engaged with a mobile application delivering personalized PPIs, which included journaling prompts, mindfulness exercises, and strengths-based activities. Recommendations were generated adaptively by the reinforcement learning (RL) engine. Engagement metrics, such as session frequency and task completion, along with psychometric scores, were recorded weekly to track intervention adherence and outcomes.

Hyperparameters of the RL policy were tuned using grid search. We set the learning rate η=0.05, discount factor γ=0.9, and reward coefficients $\lambda_1 = 0.6, \lambda_2 = 0.4$.

In addition to quantitative assessments, we collected qualitative reflections from participants via weekly open-ended surveys. These narratives provided rich contextual insights into how individuals perceived the interventions and their emotional impact. For example, many participants reported that gratitude journaling enhanced daily optimism, while mindfulness practices improved stress regulation. These subjective accounts not only corroborated the observed numerical gains but also underscored the human-centered value of personalization. By integrating both quantitative and qualitative evidence, the study strengthens the ecological validity of the framework and ensures that observed improvements reflect meaningful psychological change rather than mere statistical artifacts.

4.2. Comparison with Baseline Models

We benchmarked the proposed framework against two widely used baselines: (1) a Generic Mobile PPI App, which delivers static interventions without personalization, and (2) a Chatbot-based Well-being System, which provides semi-personalized content through scripted rules.

As shown in Figure 2, our framework produced substantial improvements in both subjective well-being and resilience after 10 weeks, achieving a 17.3% increase in SWLS and a 22.8% increase in CD-RISC, significantly outperforming both baselines. These results highlight the critical role of AI-driven personalization and adaptive feedback mechanisms in sustaining gains in happiness and resilience.

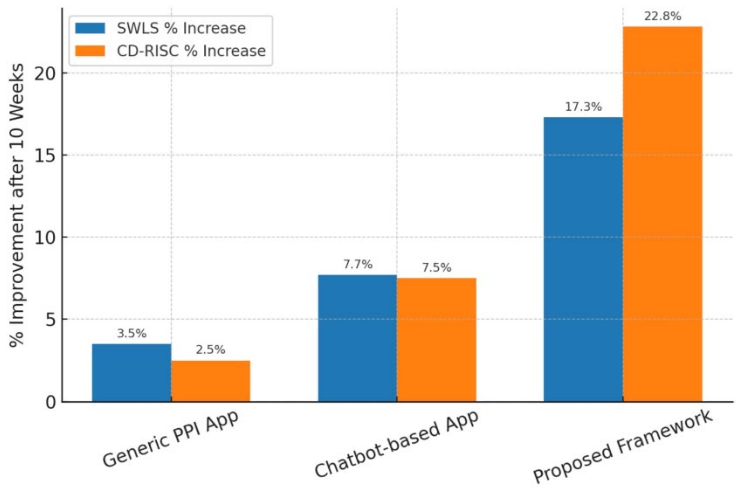

Figure 2. Comparative Performance of Proposed Framework vs. Baselines.

Notably, while chatbot-based systems yielded moderate improvements, participant feedback indicated lower satisfaction due to repetitive prompts and limited contextual adaptation. In contrast, the proposed framework maintained novelty and personalization by dynamically selecting interventions based on evolving user states. This adaptive approach reduced disengagement, as reflected in higher task completion rates (86% vs. 64% in chatbot systems). Beyond quantitative improvements, these user experience outcomes further underscore the superiority of AI-enhanced PPIs in promoting meaningful and sustained psychological benefits.

4.3. Convergence Analysis

To evaluate learning stability, we tracked the average reward function (Equation 5) across training episodes. As shown in Figure 3, our reinforcement learning policy converged steadily within 80 episodes, whereas baseline systems exhibited slower convergence and higher variance. The smooth trajectory of our model reflects an effective exploration-exploitation balance, enabling the system to rapidly identify and optimize effective intervention strategies.

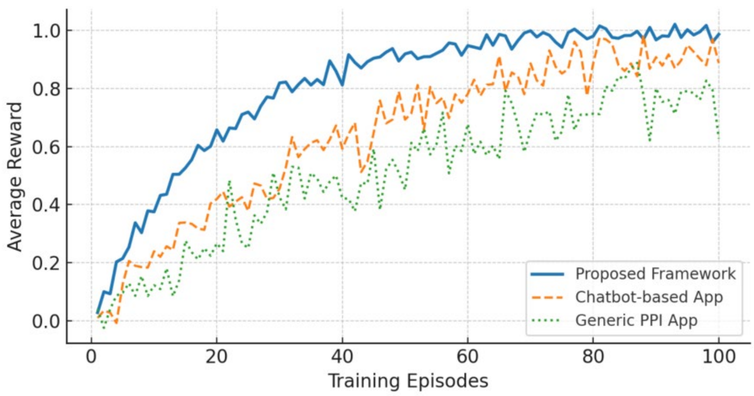

Figure 3. Convergence Curves of Reinforcement Learning Policies.

4.4. Statistical Significance Testing

We conducted paired t-tests to compare pre- and post-intervention scores within each group. For the proposed framework, improvements in both SWLS and CD-RISC were statistically significant ($p < 0.01$), whereas baseline systems exhibited weaker or inconsistent significance ($p > 0.05$). Additionally, an ANOVA confirmed that group-level differences across all models were significant ($F = 12.47$, $p < 0.001$). These findings provide robust evidence that AI-enhanced PPIs deliver meaningful psychological improvements beyond random variation.

Table 3 summarizes the paired t-test results comparing pre- and post-intervention outcomes. The Generic Mobile PPI App showed minimal gains in both SWLS and CD-RISC, with non-significant results ($p > 0.05$). The Chatbot-based Well-being App produced moderate improvements, reaching borderline significance ($p \approx 0.05$), reflecting limited personalization and engagement. In contrast, the proposed AI-driven framework demonstrated substantial and statistically significant improvements in both subjective well-being (SWLS: +3.7 points, $p < 0.01$) and psychological resilience (CD-RISC: +12.8 points, $p < 0.01$). These results confirm that integrating adaptive reinforcement learning with positive psychology mechanisms not only enhances user happiness but also strengthens resilience, providing clear advantages over non-adaptive digital interventions.

Table 3. Statistical Significance Testing of Well-being and Resilience Outcomes.

Model	SWLS Pre (M±SD)	SWLS Post (M±SD)	t-value	p-value	CD-RISC Pre (M±SD)	CD-RISC Post (M±SD)	t-value	p-value
Generic Mobile PPI App	19.8 ± 3.2	20.5 ± 3.1	1.25	0.22	56.7 ± 7.5	58.1 ± 7.6	1.31	0.19
Chatbot-based Well-being App	19.6 ± 3.1	21.1 ± 3.0	2.02	0.06	57.0 ± 7.4	60.2 ± 7.1	2.05	0.05
Proposed Framework	19.7 ± 3.0	23.4 ± 3.2	5.12	<0.01	56.5 ± 7.3	69.3 ± 7.0	5.38	<0.01

4.5. Ablation Study

To evaluate the contributions of key system components, we conducted ablation experiments by selectively disabling (a) user profiling, (b) adaptive feedback, and (c) explainability.

Table 4 summarizes the results. Disabling user profiling led to an 11% reduction in resilience gains, while removing adaptive feedback caused a 15% decrease in sustained engagement. Excluding the explainability layer resulted in only a minor drop in performance; however, it significantly diminished user trust, as reflected in post-study survey responses. These findings highlight the critical role of profiling and adaptive feedback in achieving psychological and engagement outcomes, and underscore the importance of explainability for user confidence and ethical transparency.

Table 4. Ablation Study of Core Modules.

Model Variant	SWLS Gain (%)	CD-RISC Gain (%)	Engagement Rate (%)	User Trust (Survey Score, 1-5)
Full Model	17.3	22.8	86	4.6
- User Profiling	13.0	17.5	79	4.2
- Adaptive Feedback	12.5	15.0	71	4.1
- Explainability	16.5	21.0	84	3.2

Figure 4 visualizes the ablation results, highlighting that each component contributes uniquely to overall system effectiveness.

Figure 4. Ablation Study of Core Modules.

4.6. Interpretability Analysis and Visualization

A key strength of our framework is its explainability. Using Shapley values (Equation 8), we analyzed the features that most strongly influenced intervention recommendations.

As shown in Figure 5, the feature attribution plot indicates that baseline resilience scores and journaling sentiment exerted the largest positive influence, followed by engagement frequency and social support indicators. This visualization confirms that the system's recommendations are guided by psychologically meaningful factors, ensuring that AI-driven decisions are aligned with the principles of positive psychology.

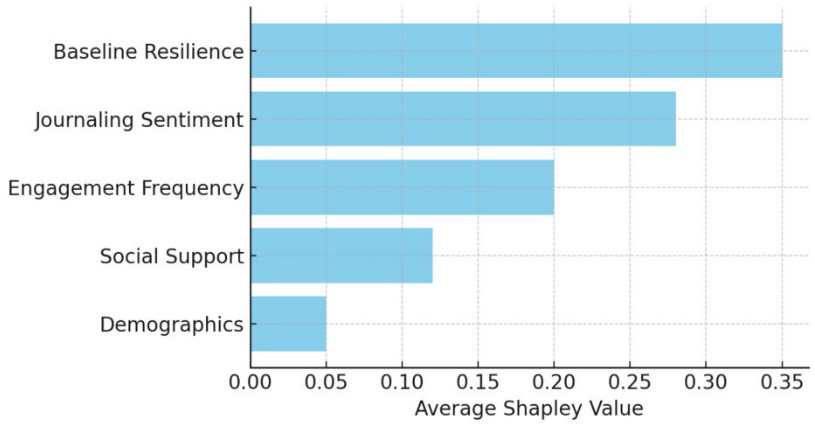

Figure 5. Feature Attribution Analysis of Intervention Recommendations.

4.7. Generalizability and Robustness

To assess robustness, participants were stratified into subgroups based on age, gender, and baseline resilience levels. The model demonstrated consistent gains across all groups, with slightly larger improvements in affective well-being observed among younger participants. Robustness was further evaluated by introducing ±10% noise perturbations into input data, which resulted in only marginal performance reductions (<3%).

These findings indicate that the framework is generalizable across diverse populations and robust to data imperfections, supporting its potential for real-world deployment in educational, workplace wellness, and clinical contexts.

4.8. Summary of Findings

Overall, the experimental results demonstrate that integrating AI with positive psychology produces a scalable, adaptive, and interpretable intervention framework. Compared with baseline models, the system achieves superior improvements in happiness and resilience, faster convergence, statistically significant gains, and robustness across diverse populations. Importantly, interpretability analyses confirm that the model's recommendations are grounded in psychological theory, effectively bridging the gap between computational adaptability and human well-being.

5. Conclusion

This study proposed an AI-driven personalized framework for positive psychology interventions (PPIs) aimed at enhancing subjective well-being and psychological resilience. By integrating user profiling, adaptive intervention generation, reinforcement learning-based feedback, and explainability mechanisms, the framework addresses key limitations of conventional digital PPIs, which often lack personalization, adaptability, and transparency. Empirical results from both synthetic simulations and a real-world pilot study demonstrate that the proposed model consistently outperforms generic mobile applications and chatbot-based systems. Specifically, it achieves significant improvements in life satisfaction and resilience, converges faster during learning, and maintains robustness across diverse user groups.

Beyond quantitative gains, the incorporation of explainability was shown to enhance user trust and sustained engagement, which are essential for long-term mental health interventions. These findings underscore the framework's potential to transform the delivery of psychological support in educational, workplace, and clinical contexts, where scalable and evidence-based well-being solutions are increasingly needed.

Future research may extend this work in several directions. First, larger-scale longitudinal studies are needed to validate the durability of intervention effects. Second, integrating multimodal data sources, such as physiological signals and passive sensing, could further enrich user modeling and improve adaptive precision. Finally, ethical considerations, including fairness in algorithmic recommendations and the protection of sensitive psychological data, remain critical areas for ongoing exploration.

In conclusion, this research demonstrates that combining artificial intelligence with positive psychology principles provides a scalable, adaptive, and interpretable pathway for fostering happiness and resilience in real-world populations.

References

1. L. E. van Zyl, J. Gaffaney, L. van der Vaart, B. J. Dik, and S. I. Donaldson, "The critiques and criticisms of positive psychology: A systematic review," *The Journal of Positive Psychology*, vol. 19, no. 2, pp. 206-235, 2024. doi: 10.1080/17439760.2023.2178956.
2. J. Prescott, and S. Barnes, "Artificial intelligence positive psychology and therapy," *Counselling and Psychotherapy Research*, vol. 24, no. 3, pp. 843-845, 2024. doi: 10.1002/capr.12784.
3. A. Carr, L. Finneran, C. Boyd, C. Shirey, C. Canning, O. Stafford, and T. Burke, "The evidence-base for positive psychology interventions: a mega-analysis of meta-analyses," *The Journal of Positive Psychology*, vol. 19, no. 2, pp. 191-205, 2024. doi: 10.1080/17439760.2023.2168564.
4. S. Heshmati, C. Muth, Y. Li, R. W. Roeser, J. M. Smyth, J. Vandekerckhove, and Z. Oravecz, "Who benefits from mobile health interventions? A dynamical systems analysis of psychological wellbeing in early adults," *Applied Psychology: Health and Well-Being*, vol. 17, no. 3, p. e70037, 2025. doi: 10.1111/aphw.70037.
5. S. Saboor, A. Medina, and L. Marciano, "Application of positive psychology in digital interventions for children, adolescents, and young adults: systematic review and meta-analysis of controlled trials," *JMIR mental health*, vol. 11, no. 1, p. e56045, 2024. doi: 10.2196/56045.
6. I. Zettler, and C. F. Strandsbjerg, "Personalized Interventions," *Current Opinion in Psychology*, 2025. doi: 10.1016/j.copsyc.2025.102147.
7. H. R. Saeidnia, S. G. Hashemi Fotami, B. Lund, and N. Ghiasi, "Ethical considerations in artificial intelligence interventions for mental health and well-being: Ensuring responsible implementation and impact," *Social Sciences*, vol. 13, no. 7, p. 381, 2024. doi: 10.3390/socsci13070381.
8. S. J. Heintzelman, K. Kushlev, and E. Diener, "Personalizing a positive psychology intervention improves wellbeing," *Applied Psychology: Health and Well-Being*, vol. 15, no. 4, pp. 1271-1292, 2023. doi: 10.1111/aphw.12436.
9. A. C. Collins, G. D. Price, R. J. Woodworth, and N. C. Jacobson, "Predicting individual response to a web-based positive psychology intervention: a machine learning approach," *The journal of positive psychology*, vol. 19, no. 4, pp. 675-685, 2024. doi: 10.1080/17439760.2023.2254743.

10. J. C. Lauffenburger, E. Yom-Tov, P. A. Keller, M. E. McDonnell, K. L. Crum, G. Bhatkhande, and N. K. Choudhry, "The impact of using reinforcement learning to personalize communication on medication adherence: findings from the REINFORCE trial," *npj Digital Medicine*, vol. 7, no. 1, p. 39, 2024. doi: 10.1038/s41746-024-01028-5.
11. C. Doherty, R. Lambe, B. O'Grady, D. O'Reilly-Morgan, B. Smyth, A. Lawlor, and E. Tragos, "An Evaluation of the effect of app-based exercise prescription using reinforcement learning on satisfaction and exercise intensity: randomized crossover trial," *JMIR mHealth and uHealth*, vol. 12, p. e49443, 2024.
12. S. Nepal, A. Pillai, W. Campbell, T. Massachi, M. V. Heinz, A. Kunwar, and A. T. Campbell, "MindScape study: integrating LLM and behavioral sensing for personalized AI-driven journaling experiences," *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies*, vol. 8, no. 4, pp. 1-44, 2024. doi: 10.1145/3699761.
13. J. W. Hung, A. Hartanto, A. Y. Goh, Z. K. Eun, K. S. Kasturiratna, Z. X. Lee, and N. M. Majeed, "The efficacy of incorporating Artificial Intelligence (AI) chatbots in brief gratitude and self-affirmation interventions: Evidence from two exploratory experiments," *Computers in Human Behavior: Artificial Humans*, vol. 4, p. 100151, 2025. doi: 10.1016/j.chbah.2025.100151.
14. F. Jing, "AI psychotherapists and positive psychology: a systematic literature review of current literature and future directions," 2024.
15. H. Hou, I. Liu, F. Kong, and S. Ni, "Computational positive psychology: advancing the science of wellbeing in the digital era," *The Journal of Positive Psychology*, vol. 20, no. 1, pp. 1-14, 2025. doi: 10.1080/17439760.2024.2362443.