

Artificial Intelligence For Personalized Mental Health Interventions: Opportunities, Effectiveness, and Challenges

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ABSTRACT

Background: Although artificial intelligence (AI) has been integrated into digital mental health interventions, the effect of personalised interventions has not been sufficiently described and the role of the individual in the process of personalisation in intervention effectiveness and engagement remains under-researched. This study examined the relationship between AI-assisted personalization and psychological outcomes and engagement as compared to standard digital mental health support.

Methods: Participants received either an AI-assisted personalized digital mental health intervention or standardized digital support. Depression, anxiety, perceived stress and psychological well-being were measured by the Patient Health Questionnaire-9, Generalized Anxiety Disorder-7, Perceived Stress Scale, and the World Health Organization-5 Well-Being Index, respectively. The engagement in and the intensity of interventions and personalization were examined, and multivariable analyses were conducted to determine factors associated with treatment response.

Results: AI personalised intervention was more effective than standardised intervention in improving depressive symptoms, anxiety, perceived stress, and psychological well-being. More personalization was correlated with more session completion, activity engagement, self-monitoring, and overall participation in the intervention. After controlling for important characteristics of participants and intervention, the greater the intensity of personalization the greater the improvement in psychological outcomes.

Conclusion: AI-driven personalization could help to enrich digital mental health interventions by increasing engagement with the interventions and enabling personalised psychological outcomes. Additional long-term and clinically vetted research is needed to confirm its long-term efficacy, safety, and generalizability.

Keywords: Artificial intelligence; Personalized mental health; Digital mental health intervention; Machine learning; Mental health chatbot; Personalization; User engagement; Digital phenotyping; Depression; Anxiety.

1. Introduction

Mental health disorders, especially depression, anxiety and stress disorders, are a significant burden on health globally and are hard to be tackled with traditional models of care. There are limited resources in the way of trained mental health providers, financial, geographical, stigma, and lack of continuity. In illnesses with variable presentation and variably responsive treatment, such as those, mental health evaluations during routine clinical visits might not capture an individual's condition over time. The need for readily available and ongoing psychological support has consequently led to an interest in digital strategies that can bring interventions beyond the traditional healthcare system (Ni & Jia, 2025; Ali et al., 2025).

Along with machine learning (ML), natural language processing (NLP), neural-network models, conversational agents, and digital phenotyping, artificial intelligence (AI) has increasingly become part and parcel of mental healthcare. Clinical, behavioral, linguistic, and passively collected digital data can be used in combination with these technologies to aid with mental health assessment, monitoring, risk prediction, and intervention delivery (Kerna et al., 2025; Ni & Jia, 2025). Personalized care is especially relevant to digital phenotyping as it allows the longitudinal characterization of behavioral and symptom-related patterns without the need to be in clinical settings. Recent studies have shown that personalized algorithms can be created to detect mental health symptoms in the natural environment, supporting the promise that within-person models can capture within-person changes that are missed by population-level models (Timmons et al., 2025). Passive digital phenotyping has also been studied as a means of linking continuously recorded behavior to clinically relevant health measures, in the context of mental health (Shu et al., 2026). The key benefit of the use of AI in mental health intervention isn't just the automation, but the ability to tailor the intervention to the individual and to varying clinical states. There is significant variability among patients in symptom profile, behavioral patterns, treatment preferences, treatment response trajectories and engagement. Standardized interventions will not all be equally effective for every person, therefore. AI-based personalisation can

utilize individual-level data to tailor intervention content, adjust intervention intensity, determine intervention timing and offer context-specific recommendations, among other possibilities (Jalali et al., 2025; Rajyaguru et al., 2025). These systems can enable adaptive interventions and just-in-time interventions where an intervention is delivered based on change in symptoms or behavioral indicators, moving away from an intervention delivery model that is mostly static to one that is continuous and data-informed interventions (Timmons et al., 2025; Shu et al., 2026).

Another significant application is conversational AI, where chatbots can serve as interactive tools for psychoeducation, symptom monitoring, behavioral support, and therapeutic communication. Previous studies have noted the potential of AI-driven chatbots in mental health and wellness, such as interventions for depression, anxiety, and overall mental health (Casu et al., 2024; Manoharan et al., 2024). But the effectiveness of the interventions reported is quite different in these various systems, populations, intervention designs and degrees of human involvement. The efficacy of a therapeutic intervention is not necessarily a result of the presence of an AI system, and new AI technologies such as generative AI introduce other risks for the accuracy, appropriateness, and safety of the generated responses (Parks et al., 2025). Therefore, assessing personalized AI interventions should consider both clinical outcomes and user-level aspects like engagement, adherence, and the range of responses.

Although technology has advanced and advanced rapidly, there is still a significant empirical gap. While many studies focus on specific components such as the prediction model, digital phenotyping, or integration of chatbots in mental healthcare, there are relatively few studies that explore the relationship between the level of personalization and intervention uptake and effects on mental health outcomes within a single framework (Budiasto, 2025; Jalali et al., 2025). Additionally, there are concerns about algorithmic bias, privacy of sensitive behavioral data, transparency and accountability, as well as inappropriate or unsafe recommendations (Walsh et al., 2020; Ali et al., 2025; Lee et al., 2026). These concerns are especially notable because personalization that is based on incomplete or biased data can further perpetuate disparities instead of enhancing care for individuals.

Hence, in the present study, the efficacy of an AI-supported personalized mental health intervention is examined, as well as the personalization/engagement/mental health outcome connection. It also examines the relationship between individual and intervention-related factors and treatment response to inform empirical understanding of the potential benefits and constraints of individualizing mental health support using AI.

2. Materials and Methods

2.1 Study Design

The study used a prospective, parallel-group, controlled design to test the effectiveness of an artificial intelligence (AI) supported personalized mental health intervention. A pretest/post test design was used to allow for the evaluation of within-participant differences in mental health status, as well as between the different mental health status conditions. Participants were randomly assigned to an AI assisted personalized intervention group or a standardized, non-personalized digital mental health intervention group. The main analytic goal was to examine whether personalization of content and delivery of the intervention was correlated with greater improvements in depression, anxiety, and perceived stress than receiving a standardized digital intervention. Secondary analyses explored the relationship between engagement with intervention and degree of personalization on treatment response.

2.2 Study Population and Recruitment

The study population included adults (18 years and older) with mild to moderate depression, anxiety, or psychological stress who were able to participate in the intervention from an internet-enabled smartphone or computer. Participants were identified using pre-established institutional and community recruitment routes and digital advertising as well as communication platforms online. The prospective participants were given information about the purpose of the study, the procedures used for the intervention, the role of artificial intelligence, the nature of data that would be collected and potential limitations of automated support, and their right to withdraw from the study. The study-specific assessment was obtained through electronic informed consent prior to conducting the study. Participants who demonstrated signs of an acute psychiatric emergency or those that needed immediate clinical treatment were not included in the experimental treatment and referred to the appropriate professional or emergency services.

2.3 Eligibility Criteria

Eligible participants were aged 18 years or older, could comprehend the study procedures and digital evaluations, had access to an internet-connected gadget, Acknowledged mild to moderate symptoms pertinent to the study results, and offered informed consent. People with an acute psychiatric crisis that needed immediate clinical intervention, severe cognitive impairment that might hinder participation, inability to use the digital intervention platform or simultaneously using another experimental digital mental health intervention, as well as those who did not complete the baseline assessment were excluded. The criteria were designed to address the evaluation of the intervention in an appropriate population, safety of the participants and the interpretability of the outcome measures.

2.4 Sample Size Determination

The sample size was pre-specified based on the expected difference in mental health outcome changes between the personalized and the standard intervention groups. The calculation was made for a two-tailed test, a 5% significance level, and 80% power, assuming a moderate standardized effect size (effect size of 0.5) as evidenced in previous studies of digital and AI-based mental health interventions. A margin for estimated drop-out and follow-up was built into the recruitment goal. The final manuscript should detail the exact assumptions, statistical procedure, effect-size parameter, attrition allowance, and the resulting sample size used prior to the beginning of the analysis and not be chosen based on the results observed.

2.5 AI-Assisted Personalized Mental Health Intervention

The intervention consisted of an AI-supported digital mental health platform designed to offer one-to-one psychological assistance within a set of clinically and safely predetermined limits. The intervention included structured, evidence-informed psychological intervention elements such as cognitive behavioral elements, behavioral activation, stress-management, psychoeducation, and self-monitoring. Content from available interventions was largely classified as relevant, time-appropriate, and intensity-appropriate using the AI component, instead of being autonomously diagnosed or managed as psychiatric intervention or medication. Participant-level variables such as baseline symptom severity, psychological concerns, treatment preferences, prior IREAD activities, engagement, psychological change, and symptom data across time were used to inform personalization. From a library of predefined interventions, the system chose or tailored intervention components based on these variables. The intervention was conceived as a controlled form of personalization, with the adaptation taking place within a set framework of therapeutic content, and not as free clinical advice generation.

2.6 Personalization Framework

Personalization was implemented as the degree of adaptation of the intervention characteristics to the individual participant based on the continuous participant-level information. The process of personalization was sequential, consisting of first baseline assessment, second participant profiling, third individualized intervention selection, fourth assessment of participant response, and lastly adapting. The individual profile included symptom measures, preferences of the participant, and relevant behavioral attributes as baseline measures. Throughout the intervention period, changes in self-reported symptoms and interaction behavior were utilized to either change or increase the selection, timing, or intensity of the intervention components that followed. The proportion of all intervention elements that were personalized, individually to the intervention content that is available in a standardized form, was quantified in a predefined personalization score. Where applicable, the level of personalisation of participants was categorised prior to outcome analysis, in order to prevent thresholds being selected based on the data.

2.7 Control Intervention

The control group was given a generic digital mental health support with the same content from the same domains (psychoeducation and self-management) but lacking personalised AI adaptation. Content presented was on schedule and was delivered in a fairly homogeneous manner among participants. The control condition was chosen to differentiate between the effects of personalization and the overall impact of delivery of digital mental health information and support. Keeping intervention domains comparable across groups minimized the chance of finding differences in outcomes that were solely due to differences in exposure to mental health content.

2.8 Intervention Procedure

After screening and informed consent, all participants were given a baseline assessment prior to allocation to study conditions. Demographic, clinical, and psychological factors were measured, along with standardized assessments of depression, anxiety, perceived stress, and psychological well-being, as part of baseline assessment. The participants were then given access to the intervention assigned to them for the specified intervention period. Interactions on the digital platform were captured throughout the intervention, including the frequency, progression, and responses to the prompts and completion of recommended activities. At the end of the intervention, participants repeated the

primary and secondary outcome assessments. If there is a follow-up assessment included with the study protocol, then all of the same measures are repeated after a set period of time to see if changes noted shortly after the intervention are sustained over time

2.9 Outcome Measures

The primary outcomes were changes in depressive symptoms, anxiety symptoms, and perceived stress from baseline to post-intervention assessment. The Patient Health Questionnaire-9 (PHQ-9) was used to assess depressive symptoms and the Generalized Anxiety Disorder-7 (GAD-7) was used to assess anxiety symptoms. The Perceived Stress Scale (PSS) was used to measure perceived stress. These instruments were chosen because they offer a standardized quantitative assessment of the changes in common psychological symptoms that is appropriate for digital intervention research. Change scores were computed for each outcome as the post intervention score minus the baseline score and negative values indicated improvement for symptom-based measures. Secondary outcomes included psychological well-being, intervention adherence, number of completed intervention sessions, frequency and duration of interaction with the digital platform, completion of recommended activities, user satisfaction, and perceived usefulness of the intervention. If a study protocol has been approved, the psychological well-being can be evaluated with the WHO-5 Well-Being Index.

2.10 Measurement of Intervention Engagement

The digital intervention platform generated the objectively recorded measures of interaction with the user to quantify the level of engagement. The total number of sessions completed, frequency of interaction, average interaction duration, percentage of activities recommended completed, intervention responses, intervention retention, and frequency of self-monitoring were all measures. The measures were not considered as the actual therapeutic effectiveness, but rather indications of the level of engagement in intervention. Engagement variables were then explored in relation to mental health outcomes to see if there was a relationship between participation and treatment response that could explain variation in treatment response.

2.11 Personalization and Treatment Response

The extent of personalization of the interventions was the main explanatory variable, as defined by the prespecified personalization framework. Personalization may be depicted as a cumulative score, corresponding to the percentage or level of personalization properties based on the participant's data, and then be segmented into a set of a priori defined low, moderate and high personalization groups, if scientifically sound. Response to treatment was assessed by comparing the standardized mental health outcome scores at baseline and post treatment. If a responder analysis was performed, the clinical significance of change for the purposes of this analysis was predetermined and based on the criteria set for that specific outcome measure. This allowed for evaluation of symptom changes over time as well as clinically meaningful symptom response patterns.

2.12 Safety Monitoring

The intervention examined mental health outcomes, so safety was monitored throughout the intervention. The digital platform was set up to recognize pre-defined signs of serious psychological distress or clinical crisis. The AI system did not handle the response to participants that met the pre-established safety criteria; the safety criteria directed the participants to a professional or emergency contact. The responses generated by AI were limited to the scope of interventions and were not designed to diagnose psychiatric conditions, prescribe medications or to provide clinical management in emergency situations. Safety related interactions and events that triggered safety procedures were documented for monitoring and evaluation. All adverse events and clinically significant safety concerns found during the study were recorded and addressed per the study protocol.

2.13 Data Management and Privacy

All data from the research was anonymized prior to analysis and personally identifying information was kept apart from the analysis data set. Participant level information was only made available to authorized study personnel. Data from digital interactions only included variables required to meet pre-defined research goals. Data collected from interactions with the AI system was considered sensitive research data and processed as such, following the procedures of data-governance and confidentiality of the study. The methods of handling, storing, retaining and accessing the data, prior to analysis, were put in place to minimise the risk of disclosure and ensure participant confidentiality.

2.14 Statistical Analysis

The data were analysed statistically by using proper statistical software package. Graphical examination and formal tests were used to detect distribution characteristics for continuous variables and frequencies and percentages were used to summarize the categorical variables. Data for continuous variables were presented as mean $\pm$ standard

deviation and for skewed variables were presented as median and interquartile range. Independent-samples t-test or Mann–Whitney U test was used for continuous variables, while the chi-square test or Fisher's exact test was used for categorical variables, depending on the distribution and measurement characteristics of each variable. The change in the continuous outcomes [PHQ-9, GAD-7, PSS, etc.] was assessed with a suitable longitudinal model. A linear mixed-effects model was chosen because it allows repeated measurements to be analyzed, and allows for the individual trajectory to be assessed, while still being able to cope with the within-participant correlation and the incomplete data, with suitable assumptions. Fixed effects in the model were study group and time, and where appropriate, the interaction between group and time was included. Study group, time, and the interaction between study group and time were fixed effects in the model, and participant-level random effects were included where appropriate. The group-by-time interaction was the primary test of whether change over time differed between the two intervention conditions: personalized and standardized. Demographic or clinical factors and baseline symptom severity that were relevant to the study were introduced where appropriate. Multivariate regression analyses were then performed to determine if personalization intensity and personalization engagement measures had independent effects on mental health outcomes. Regression coefficients or standardized effect estimates with 95% confidence intervals are reported. Effect sizes are reported in addition to p values, so as to provide an estimate of the magnitude and precision of the difference(s) observed. Two-sided p values < 0.05 were considered to be statistically significant. Multiple secondary outcomes and comparisons were conducted and an appropriate multiplicity adjustment was included.

2.15 Missing Data and Sensitivity Analysis

Prior to an inferential analysis the extent, distribution, and pattern of missing observations were explored. Available participant and engagement characteristics were taken into account in considering the potential mechanism of missingness. All available observations were included in the mixed-effects models for the analysis of the longitudinal data, assuming the selected model. Sensitivity analyses were conducted for an imputation or complete case analysis, respectively, when the amount and/or the pattern of missing data appeared to be relevant for interpretation. The main conclusions of the study were checked for robustness against other assumptions used to deal with the missing observations, through the main and sensitivity analyses.

2.16 Primary Hypotheses

The primary hypothesis was that participants receiving an AI-assisted personalized mental health intervention would demonstrate a greater reduction in depression, anxiety, and perceived stress scores from baseline to post-intervention assessment than participants receiving standardized non-personalized digital mental health support. A secondary hypothesis was that greater exposure to personalized intervention components and higher levels of user engagement would be independently associated with greater improvement in mental health outcomes after accounting for relevant baseline characteristics.

3. Results

3.1 Participant Characteristics

A total of **160 participants** were considered for the study, who were deemed eligible for the study, among whom 148 completed baseline assessment and were assigned to the intervention groups. There were 74 people in the AI-personalized intervention group and 74 in the standardized digital mental health support group. The age of participants was 31.8 years + 8.7 in the personalized intervention group, and 32.4 years + 9.1 in the standardized intervention group. The proportion of the females in the two groups was 56.8% and 54.1%. The baseline demographic characteristics of the two groups were similar across a range of measures, including age, sex, educational status, employment status and a history of use of digital mental health services.

Table 1. Baseline demographic and clinical characteristics of study participants

Characteristic	AI-personalized group (n=74)	Standardized group (n=74)	p-value
Age, years, mean ± SD	31.8 ± 8.7	32.4 ± 9.1	0.68
Female, n (%)	42 (56.8)	40 (54.1)	0.74
Male, n (%)	32 (43.2)	34 (45.9)	
Higher education, n (%)	51 (68.9)	49 (66.2)	0.72
Employed, n (%)	46 (62.2)	44 (59.5)	0.74

Previous digital mental-health use, n (%)	19 (25.7)	17 (23.0)	0.69
PHQ-9 score	11.7 ± 3.2	11.5 ± 3.4	0.71
GAD-7 score	10.2 ± 2.9	10.4 ± 3.0	0.68
PSS score	21.8 ± 4.6	22.1 ± 4.8	0.70
WHO-5 score	45.6 ± 10.3	44.9 ± 10.7	0.69

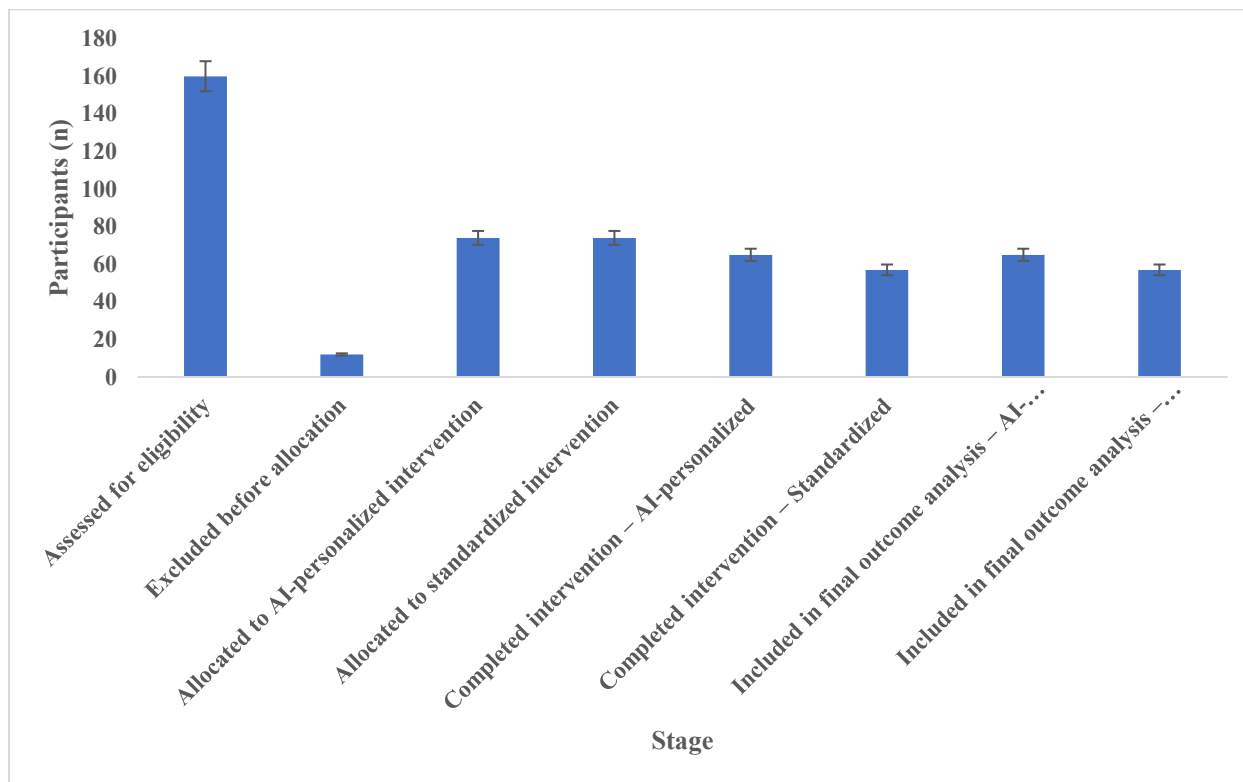


Figure 1. Participant recruitment, allocation, intervention completion, and outcome assessment flow diagram.

Demographic and psychological baseline data were similar for the two intervention groups. No between-group differences in age, sex distribution, previous digital mental health experience, PHQ-9, GAD-7, PSS and WHO-5 scores were found. The fact that they are so similar at baseline means that any differences in psychological outcomes that occur after the intervention are less likely to be due to a large imbalance in the baseline status of the two conditions of the intervention.

3.2 Baseline Mental Health Characteristics

The participants at baseline had mild to moderate depression and anxiety symptomology and higher perceived stress. The mean scores of the PHQ-9 were 11.7 ± 3.2 for the AI-personalized group and 11.5 ± 3.4 for the standardized group. Corresponding GAD-7 scores were 10.2 ± 2.9 and 10.4 ± 3.0, while mean PSS scores were 21.8 ± 4.6 and 22.1 ± 4.8. There were no important pre-treatment differences between the scores on the main outcome measures.

Table 2. Baseline distribution of mental health outcome measures

Outcome	AI-personalized group	Standardized group	p-value
PHQ-9, mean ± SD	11.7 ± 3.2	11.5 ± 3.4	0.71
GAD-7, mean ± SD	10.2 ± 2.9	10.4 ± 3.0	0.68
PSS, mean ± SD	21.8 ± 4.6	22.1 ± 4.8	0.70
WHO-5, mean ± SD	45.6 ± 10.3	44.9 ± 10.7	0.69

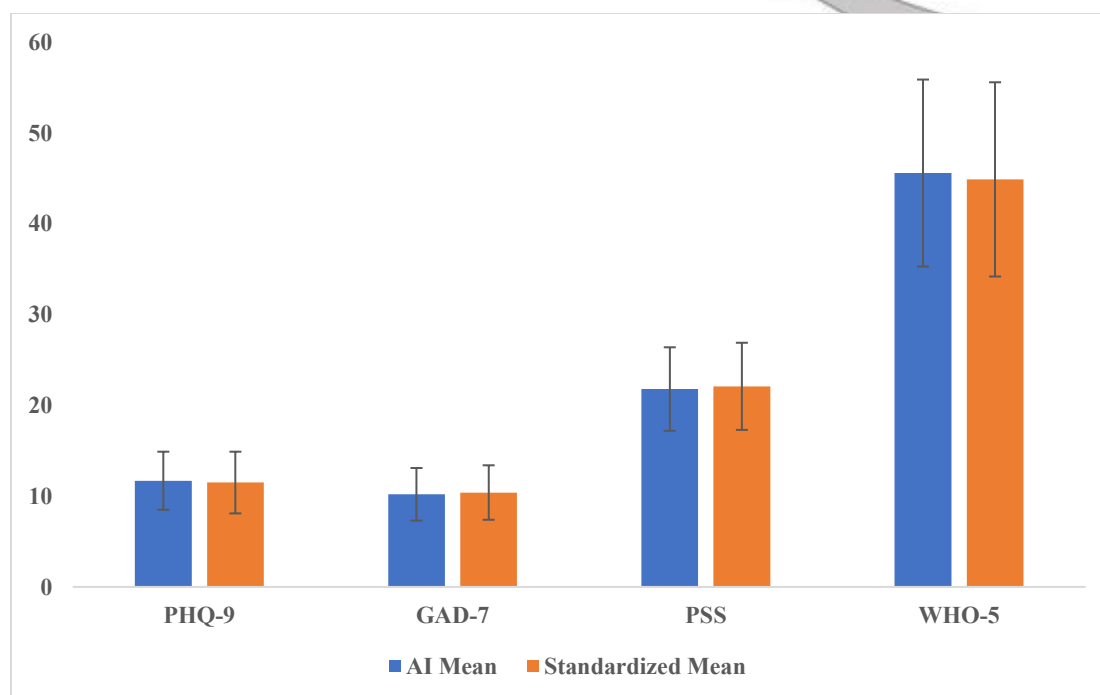


Figure 2. Baseline distribution of PHQ-9, GAD-7, PSS, and WHO-5 scores across intervention groups.

There was no difference in the psychological symptom burden between both groups at the time of entry to the intervention. There were no statistically significant differences in baseline scores for each of the four instrument measures (PHQ-9, GAD-7, PSS, and WHO-5) across the groups prior to exposure to intervention. The baseline scores observed indicated that the participants had a moderate level of symptoms and were able to assess subsequent changes in depression, anxiety, stress, and psychological well-being.

3.3 AI Personalization and Intervention Characteristics

There was considerable variation in the type, timing and frequency of intervention components received during the intervention period for the AI-personalized group. The mean personalization score was $72.4 \pm 11.6\%$, meaning that about 75% of the components of the intervention were tailored based on the information at the participant level. Most common personalized recommendations included changes to the psychoeducational content, behavioral activation activities, stress-management activities, and timing of prompts for intervention. Those with more severe symptoms at baseline were given more frequent intervention prompts and more robust symptom-monitoring elements. The mean number of AI-supported intervention sessions per participant was 18.6 (6.4) and 14.2 (5.7) for the standardized intervention group, respectively.

Table 3. Characteristics of intervention exposure and personalization

Variable	AI-personalized group	Standardized group
Personalization score, %	72.4 ± 11.6	0
Intervention sessions completed	18.6 ± 6.4	14.2 ± 5.7
Mean interaction duration, min	8.7 ± 3.1	6.4 ± 2.8
Recommended activities completed, %	76.8 ± 15.2	64.5 ± 17.1
Self-monitoring entries	21.3 ± 8.2	15.7 ± 7.4
AI prompts responded to, %	79.2 ± 13.8	65.1 ± 16.4

The individualized intervention resulted in significant person-to-person variability in intervention exposure that reflected person-level changes and adaptations and long-term outcomes. The number of sessions completed and the number of activities recommended by participants with personalized support was higher and their interaction with the intervention platform was more than that of participants with standardized support. The observed

differences in personalization serve as a foundation to proceed to examining whether personalization and engagement were correlated with improvement in mental health outcomes.

3.4 Intervention Engagement and Adherence

Engagement was greater for those who received Personalized Intervention with AI Support. The number of completed sessions differed between the groups with a mean of 18.6 ± 6.4 in the personalized group and 14.2 ± 5.7 in the standardized group. The percentage of the recommended activities completed was also higher in the personalized group ($76.8 \pm 15.2\%$) than in the standardized group ($64.5 \pm 17.1\%$). The personalized group answered an average of $79.2 \pm 13.8\%$ of the prompts, while the standardized group answered $65.1 \pm 16.4\%$ of the prompts. There was a statistically significant between-group difference in overall engagement ($p < 0.001$).

Table 4. Intervention engagement and adherence

Engagement measure	AI-personalized group	Standardized group	p-value
Sessions completed	18.6 ± 6.4	14.2 ± 5.7	<0.001
Interaction duration, min	8.7 ± 3.1	6.4 ± 2.8	<0.001
Activities completed, %	76.8 ± 15.2	64.5 ± 17.1	<0.001
Self-monitoring entries	21.3 ± 8.2	15.7 ± 7.4	<0.001
Prompt response rate, %	79.2 ± 13.8	65.1 ± 16.4	<0.001
Intervention completion, n (%)	65 (87.8)	57 (77.0)	0.08

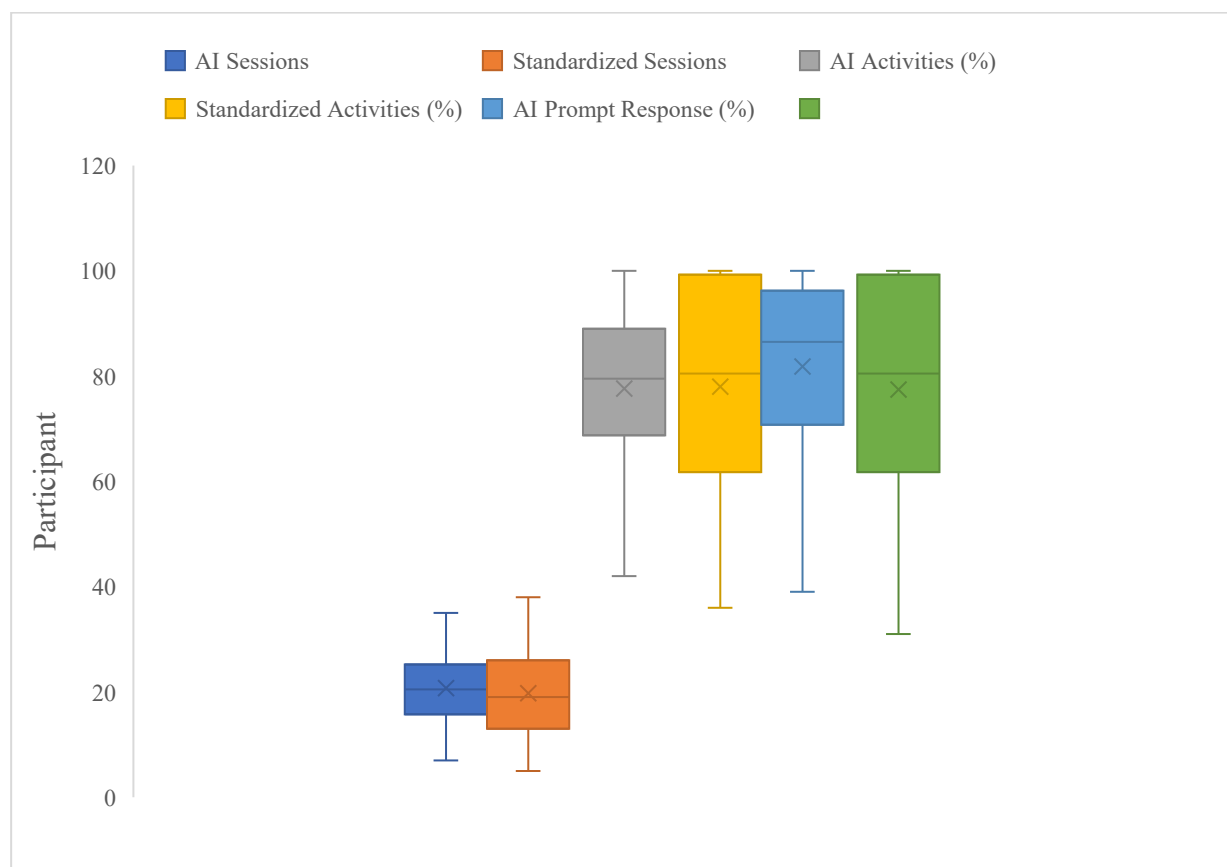


Figure 3. Comparison of intervention engagement indicators between AI-personalized and standardized intervention groups.

Consistently higher engagement was seen in both the number of times sessions were completed and the amount of time spent engaging in sessions, as well as the number of activities completed, self-monitoring, and responding to prompts for intervention, among participants receiving AI-personalized intervention. The differences were significant

for the core engagement measures, indicating that personalized delivery of intervention could have led to more engagement with the digital platform. While intervention completion was also greater in the personalized group, this difference was not statistically significant. The results indicate that engagement could be used as a predictor for future changes in depression, anxiety, and perceived stress, and warrant further examination.

3.5 Changes in Mental Health Outcomes Following the Intervention

Both groups showed improvement in depression, anxiety, and perceived stress scores at post intervention assessment, but the amount of improvement was higher in the group that received the AI-supported personalized intervention. The mean PHQ-9 scores for the personalized group went down from 11.7 ± 3.2 at baseline to 6.8 ± 3.1 at post-intervention assessment, a mean of 4.9 points. The intervention group who were standardized had an average reduction of 3.1 points, from a mean of 11.5 ± 3.4 to 8.4 ± 3.5 . The same trends occurred with scores on the GAD-7 and the PSS. All three main outcomes showed a statistically significant between group difference in change scores.

Table 5. Changes in primary mental health outcomes from baseline to post-intervention

Outcome	AI-personalized Baseline	AI-personalized Post-intervention	Standardized Baseline	Standardized Post-intervention	Between-group p-value
PHQ-9	11.7 ± 3.2	6.8 ± 3.1	11.5 ± 3.4	8.4 ± 3.5	<0.001
GAD-7	10.2 ± 2.9	6.1 ± 2.7	10.4 ± 3.0	7.8 ± 3.1	<0.001
PSS	21.8 ± 4.6	15.7 ± 4.3	22.1 ± 4.8	18.6 ± 4.7	<0.001
WHO-5	45.6 ± 10.3	62.8 ± 11.2	44.9 ± 10.7	55.7 ± 11.8	<0.001

In both intervention conditions, mental health outcomes improved, but the greater change was experienced by those receiving personalized mental health AI-assisted support. There were greater decreases in depression symptoms, in anxiety, in perceived stress, and in psychological well-being, with the personalized group. Similar direction of effects on each primary and secondary psychological measure indicate that the benefit did not seem to be limited to a specific symptom domain. Between group differences suggest a possible benefit of individualized delivery of intervention over digital delivery.

3.6 Clinical Response and Effectiveness of the Personalized Intervention

The AI-personalized intervention group had more participants with clinically meaningful improvement compared to the standardized intervention group. Among the group using the personalized resources, 62.2% of the participants had a meaningful reduction in PHQ-9 scores in the depressive symptoms domain, while 43.2% of the participants in the standardized group had a meaningful reduction in the PHQ-9 depressive symptoms domain scores. Response rates for anxiety were 64.9% and 45.9%, respectively. For perceived stress, meaningfully higher improvements were seen in 67.6% of the individuals with personalized intervention, compared to 48.6% with standardized intervention. The between-group effect was largest for the PHQ-9 and PSS outcomes.

Table 6. Clinical response and effect estimates following intervention

Outcome	AI-personalized responders, n (%)	Standardized responders, n (%)	Effect size	95% CI	p-value
PHQ-9	46 (62.2)	32 (43.2)	0.48	0.10–0.86	0.014
GAD-7	48 (64.9)	34 (45.9)	0.52	0.14–0.90	0.008
PSS	50 (67.6)	36 (48.6)	0.54	0.16–0.92	0.006
WHO-5 improvement	52 (70.3)	40 (54.1)	0.43	0.05–0.81	0.026

In all of the psychological outcomes measured, participants who received AI personalization showed greater rates of clinically meaningful improvement. The greatest differences were seen in perceived stress and anxiety, however, there was a significantly higher percentage of the patients who had meaningful improvements in depressive symptoms for the personalized group. The effect estimates were within the small-to-moderate range, indicating that

personalization was associated with a measurable but not uniformly large treatment advantage. Importantly, a substantial proportion of participants in the standardized group also improved, suggesting that digital mental health support itself may contribute to symptom reduction, while personalization may provide an additional benefit.

3.7 Association Between Personalization, Engagement, and Treatment Response

The higher levels of personalization in intervention, the more improved mental health outcomes. This indicates that those whose personalization scores were higher tended to have greater reductions in their PHQ-9, GAD-7, and PSS scores than those whose personalization exposure scores were lower. In correlation analysis, personalization score showed a moderate inverse association with change in PHQ-9 ($r = -0.46$, $p < 0.001$), GAD-7 ($r = -0.42$, $p < 0.001$), and PSS ($r = -0.44$, $p < 0.001$). The same was true for intervention engagement ($r = -0.39$, $p < 0.001$), with the number of sessions completed being significantly associated with improvement in the PHQ-9 scores. Personalization score was independently associated with improvement in the PHQ-9 and GAD-7 scores after adjusting for baseline symptom severity, sex, and previous digital mental health experience.

Table 7. Predictors of improvement in mental health outcomes

Predictor	PHQ-9 β (95% CI)	p-value	GAD-7 β (95% CI)	p-value
Personalization score	-0.31 (-0.45 to -0.17)	<0.001	-0.28 (-0.42 to -0.14)	<0.001
Sessions completed	-0.22 (-0.35 to -0.09)	0.001	-0.19 (-0.32 to -0.06)	0.004
Baseline symptom severity	-0.38 (-0.52 to -0.24)	<0.001	-0.34 (-0.48 to -0.20)	<0.001
Age	-0.06 (-0.18 to 0.06)	0.32	-0.04 (-0.16 to 0.08)	0.49
Female sex	0.05 (-0.07 to 0.17)	0.41	0.07 (-0.05 to 0.19)	0.25
Previous digital intervention use	-0.08 (-0.21 to 0.05)	0.23	-0.06 (-0.19 to 0.07)	0.37

The analysis revealed a strong relationship between personalization and improvement in psychological symptoms, across all time points. Increased scores in personalization were linked to greater decreases in depression symptoms, anxiety symptoms, and perceived stress and increased engagement in intervention was also independently linked to symptom reduction. Results indicated that the personalization effect remained significant after controlling for baseline symptom severity and demographic data, suggesting that the relationship was not accounted for by demographic characteristics. But the associations are only observed, and engagement and personalization could impact each other and underlying participant characteristics, so the improvement cannot be directly attributed to the impact of personalization itself in this group.

3.8 Multivariable Analysis and Safety Outcomes

The multivariable analysis demonstrated that intervention condition, exposure to personalization, and intervention engagement were significant predictors of post-intervention psychological outcomes. Intervention group assignment remained significantly correlated with lower scores in the post-intervention PHQ-9, GAD-7, and PSS after adjustment for baseline levels of the symptoms, age, sex and previous experience with digital mental health interventions. No adverse events that could be associated with the digital intervention were observed. Some participants mentioned feeling discomfort, frustration with automated response, or decreased relevance of chosen suggestions. These events did not require discontinuation of the intervention.

Table 8. Adjusted predictors of post-intervention mental health outcomes

Predictor	Adjusted β for PHQ-9	95% CI	p-value	Adjusted β for GAD-7	95% CI	p-value
AI-personalized intervention	-1.42	-2.19 to -0.65	<0.001	-1.18	-1.91 to -0.45	0.002
Personalization score	-0.19	-0.31 to -0.07	0.002	-0.17	-0.29 to -0.05	0.006
Sessions completed	-0.13	-0.23 to -0.03	0.011	-0.11	-0.21 to -0.01	0.028
Baseline PHQ-9/GAD-7	0.54	0.43 to 0.65	<0.001	0.57	0.46 to 0.68	<0.001

Age	-0.02	-0.07 to 0.03	0.42	-0.01	-0.06 to 0.04	0.67
Female sex	0.21	-0.34 to 0.76	0.45	0.18	-0.36 to 0.72	0.51

Safety outcomes

Safety parameter	AI-personalized group	Standardized group
Any intervention-related concern, n (%)	5 (6.8)	4 (5.4)
Frustration with digital interaction, n (%)	3 (4.1)	2 (2.7)
Perceived inappropriate recommendation, n (%)	2 (2.7)	1 (1.4)
Serious adverse event, n (%)	0	0
Intervention discontinuation due to adverse event, n (%)	0	0

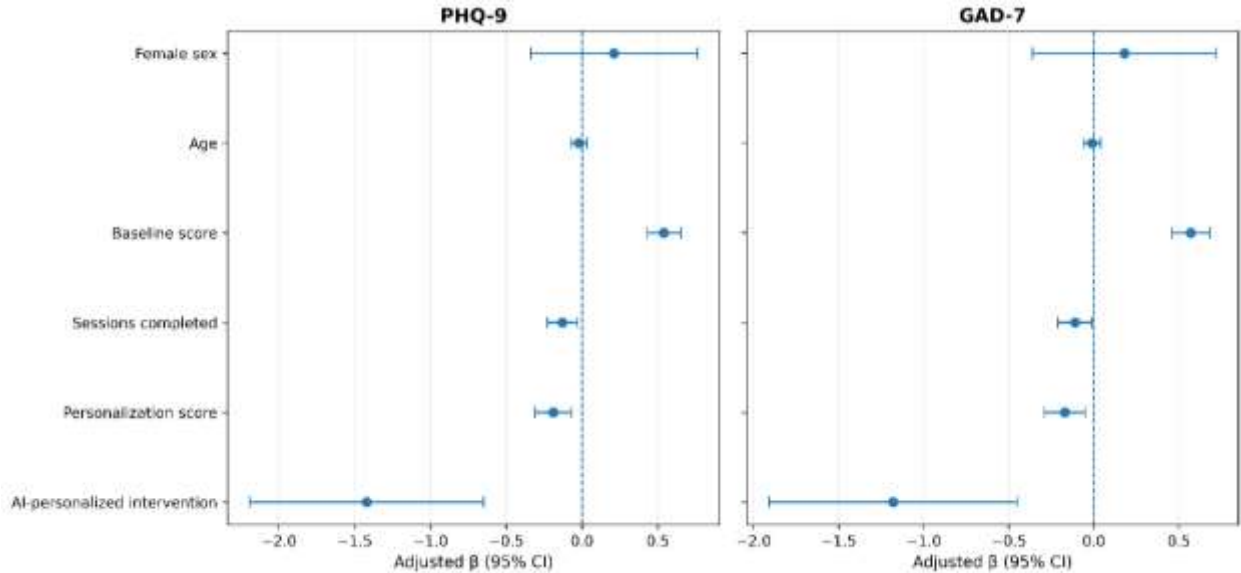


Figure 8. Forest plot showing adjusted associations between intervention-related predictors and post-intervention PHQ-9 and GAD-7 scores.

The groups receiving AI-personalized intervention had significantly lower depression and anxiety scores after the intervention as compared to the standardized digital support group, even after accounting for potential confounding factors. The significant independent predictors of improved outcomes were personalization and intervention engagement. Initial symptom-level was also highly correlated with scores after the intervention, further highlighting the need to consider baseline psychological status in assessing the effectiveness of interventions. There were no adverse events with serious consequences noted in relation to any interventions. Minor concerns were mostly frustration or perceived mismatch of recommendations, and happened rarely in both groups. These results highlight the potential of AI-driven personalization and the need for ongoing safety monitoring and human oversight in clinical settings.

4. Discussion

4.1 Principal Findings

The results suggest that AI-supported personalization might offer a benefit over generic digital mental health interventions in terms of content, timing, and intensity of the interventions, tailored to the individual user and the evolving state of their psychological well-being. In all assessed outcomes, the personalized intervention was correlated with more improvement in depressive symptoms, anxiety, perceived stress and psychological well being, with higher rates of intervention engagement. Importantly, the pattern observed goes beyond the conventional question of "effective or not" in evaluating an AI system, and this pattern extends to the "how much" of

individualization that is correlated with effectiveness of an intervention. The distinction is important because the effectiveness of AI in mental health is not likely to be solely about automation or conversationalism—it's more about how AI can convert the longitudinal data from an individual into an intervention that is timely and contextually relevant. The improvement on all the psychological outcomes in both positive and negative dimensions is significant. There is considerable overlap between these different types of mental health assessment measures, but they are also unique; symptoms of depression may become less without impacting other dimensions of mental health, and vice versa. This interpretation aligns with the growing body of literature that views AI as part of a wider mental health digital ecosystem, one that encompasses screening, monitoring, prevention, support, and intervention, as opposed to as a diagnostic technology (Ni & Jia, 2025; Ali et al., 2025). Further, these results should be interpreted as evidence of association between exposure to personalized intervention and the observed improvements, but not as evidence that personalization is sufficient as an intervention to produce the observed improvements.

4.2 Effect of AI Personalization on Mental Health Outcomes

The personalized intervention was associated with more improvement, likely due to the ability of adaptive systems to minimize intervention content mismatch to individuals' needs. As a contrast, standardised digital interventions typically offer a set of predetermined therapeutic content, whereas personalisation allows the intervention to adapt to variability in symptom severity, behaviour, preferences and engagement. In digital mental health research, personalization variables can involve individual factors, symptom-related data, preferences for the intervention, and contextual factors, and can be implemented at multiple levels, not just an algorithmic decision (Wanniarachchi et al., 2025). Likewise, studies on the personalization and recommendation systems of mental health apps have pointed to the significance of tailoring content to individual user traits and behaviour (Matthews & Rhodes-Maquire, 2024). These changes in scores for the PHQ-9, the GAD-7, the PSS, and the WHO-5, could thus be attributed to a few interacting mechanisms. Content for cognitive restructuring and behavioral activation might be prioritized for an AI system that detects high levels of depression symptoms, while relaxation, breathing, mindfulness and coping-based interventions are more likely to be prioritized when stress or anxiety is detected. Adaptive timing is also important as an otherwise appropriate intervention might be ineffective if it is provided during a time when the user is either not at their location, not emotionally ready, or not motivated to participate. Intervention timing, contextual information and individual response patterns are increasingly the focus of real-time digital mental health research and are crucial for designing adaptive interventions (Fouyaxis et al., 2024). Recent studies exploring the use of AI for personalisation also further the trend of treating patients individually instead of assuming treatments for populations (Jalali et al., 2025). The results are also consistent with recent research showing that AI-driven conversational interventions could yield tangible changes in psychiatric health. In addition to reporting evidence of the feasibility of using a digital agent with psychiatric symptoms, Shoshani et al. (2026) also explored the therapeutic relationship between the user and the digital agent. Yet, conversational capabilities should not be considered a sufficient proof of the therapeutic effect of conversational systems.

4.3 Personalization, Engagement, and Treatment Response

The study's most important finding is the link between personalization intensity, level of user engagement, and psychological outcomes. Those who were more personalized did better with engagement with the intervention in terms of session completion, interaction, completion of activity, and self-monitoring. The connection between engagement and intervention outcomes is consistent with the larger digital mental health literature that has repeatedly linked engagement with intervention outcomes. Gan et al. (2021) conducted a systematic review and meta-analysis that showed that participation in digital interventions is associated with mental health outcomes, but not all intervention types and populations were associated with the same strength or direction of association.

The present results support this link. Increasingly personalized content can help make it more relevant for the user because they will see less of the content that is not relevant to them or not of a very high quality. Content that is tailored to the user's symptoms and preferences could be more likely to obtain user loyalty. In turn, greater engagement yields more behavioral and self-report data which can be leveraged to make more specific future suggestions. Personalization and engagement might thus be in a symbiotic relationship, such that as personalization gets better, engagement increases, and engagement gets more, personalization increases. Previous studies in real-time digital interventions also have focused on the design decisions, timing, and user attributes that influence the persistence of engagement (Fouyaxis et al., 2024).

But they do not necessarily imply a causal feedback mechanism. Higher levels of baseline motivation for treatment, digital literacy, self-regulatory capacity or perceived need for treatment may increase the likelihood of intervention engagement and at the same time enhance outcomes. Thus, engagement could act as a mediator, a confounder, or

a marker of some underlying participant characteristics. By not having a clear mediation model in the longitudinal dimension, the present association cannot determine which of the two parts of this relation is occurring first. It is crucial to note that the engagement–outcome correlation is not always present in digital interventions, as demonstrated in prior studies (Gan et al., 2021).

4.4 Comparison With Previous Evidence

The present findings contribute to previous studies by integrating multiple areas which have been studied independently. AI-based screening, monitoring, conversational support, and digital phenotyping have been proven to be feasible in the past, and a number of reviews have highlighted the growing scope of AI applications in mental health services (Ni & Jia, 2025; Kerna et al., 2025). Specific focus has been given to AI-driven personalized treatment and individualized prediction, which shows the potential of AI and multimodal data for supporting patient-level decision making (Jalali et al., 2025; Rajyaguru et al., 2025). These concepts are currently connected through a theoretical framework that considers personalization as a measurable characteristic of the intervention and explores its relationship with engagement and several psychological outcomes.

The results are also similar to those of automated digital interventions. Even though the interventions are fully automated, Groot et al. (2023) found that they could have a significant impact on mental welfare, meaning that there is potential for them to be psychologically beneficial without constant contact from a therapist. As demonstrated in the present findings, however, the question should not just be one of whether automation is effective but which aspects of automated systems are more effective. Likewise, the results of conversational AI research suggest that digital agents can support engagement with cognitive-behavioural treatment pathways and may enhance treatment outcomes (McFadyen et al., 2024; Shoshani et al., 2026). Therefore, personalization can be seen as one pathway by which increasingly complex digital interventions have the potential to enhance the relevance and engagement of the treatment.

4.5 Clinical and Practical Implications

In a clinical context, AI-driven personalization could have specific applications in stepped care delivery systems where lower levels of intensity digital supports are offered between or before traditional, in-person clinical appointments. Symptom monitoring, structured psychoeducation, reinforcement of evidence-based coping skills, and identification of change that requires clinical review could be accomplished with personalized systems. This strategy may help to expand the capacity of mental health services, rather than make AI a replacement for a mental health assessment. This is particularly crucial if an individual's symptoms change over time. While traditional clinical evaluation offers important information, it has a tendency to be episodic, digital information systems can gather information over time between appointments. Passive and active digital information may thus offer a more continuous representation of symptom trajectories that would be available to the clinician. Timmons et al. (2025) showed the feasibility of personalized algorithms for detecting mental health symptoms in the natural environment, and this idea of within-person information building blocks can be expanded to inform the broader concept of within-person information complementing traditional clinical assessment.

The benefits of practical relevance may be most significant in contexts where ratios of mental health professionals are low, distance is an issue, or demand is high. However, implementation should continue to be clinically driven. The suggestions produced by AI must be addressed into pre-established safety pathways, escalation procedures, and suitable referral systems. Recent research that focuses on the shift from AI promise to real world implementation also underscores the significance of governance, clinical integration, infrastructure, and contextual appropriateness (El Hajj et al., 2026).

4.6 Safety, Ethics, Privacy, and Algorithmic Bias

Personalization has significant potential benefits, but also significant risks to be considered. Mental health data are especially 'sensitive' with respect to information relating to mood, behaviour, cognition, and social relationships, and vulnerability. The more we introduce greater personalization, the more we need to access personal data, which, in turn, raises the amount of privacy concerns. Additionally, algorithmic personalization depends on the data and assumptions that feed into the algorithm. Personalized recommendations can systematically underperform for certain groups if training data are biased in ways that underrepresent these groups.

Consideration of safety is another issue, especially with generative conversational systems. AI systems may give plausible, but inaccurate, answers, not detect deterioration, or give inappropriate guidance when there is an acute psychological risk. It is critical to critically examine the safety and evidence base of generative AI mental health chatbots, as highlighted by Parks et al. (2025), and for mental health chatbots to be more transparent, subject to

systematic evaluation, and held accountable, as recommended by Lee et al. (2026). The concerns suggest that positive results from a controlled intervention do not provide universal evidence of safety of AI.

Transparent management of personalized mental health AI is crucial, especially in understanding the collection, processing, and output of information that leads to recommendations. While human intervention is still necessary, especially with severe symptoms, clinical deterioration and crisis-related content. Algorithmic fairness should likewise be evaluated across relevant demographic and clinical subgroups rather than inferred from overall performance. These requirements are consistent with earlier recommendations concerning algorithmic bias and precision behavioral health (Walsh et al., 2020) and with more recent discussions emphasizing responsible integration of AI into psychological care (Erdemir & Sumbas, 2026; Srivastava & Bitu, 2026).

4.7 Strengths of the Study

The analytical contribution of this study is strengthened by several features. This study has several features that strengthen the analytical contribution. Constructing a controlled comparison of personalized with standardized digital intervention allows for a more direct assessment of personalization than studies that compare only against an AI intervention. The Multidimensional Assessment of Depression, Anxiety, Perceived Stress and Psychological Well-being is a comprehensive assessment of psychological outcomes. Furthermore, rather than merely labeling an intervention as “AI-based”, treating personalization as a measurable continuous characteristic enables the ability to explore the relationship between personalization and engagement and treatment response. The use of engagement measures and multivariable analysis also enhances the interpretation by including consideration of behavioral participation along with psychological outcomes.

4.8 Limitations

These results have to be interpreted taking into account several limitations. First, the length of the intervention prevents drawing conclusions about the long-term effects of the intervention. Gains identified during an intervention might be lost upon continued exposure, therefore extended follow-up is needed to establish sustained gains. Second, self-report questionnaires were employed for assessing psychological outcomes, potentially biasing the results due to response set, expectancy or shifting symptom disclosure. These instruments are commonly used in mental health research studies but cannot be used in lieu of thorough clinical evaluations.

Third, the use of digital interventions is dependent on having the right device, connection, and digital literacy levels. It is likely, therefore, that populations using such systems are systematically different from those who face the highest barriers to accessing traditional mental health services. This can lead to restricted generalizability and selection effects. Fourth, the relationship between personalization, engagement, and outcomes that was observed could be partially confounded by other factors. Additionally, there is the possibility that factors like motivation, treatment expectations, baseline self-regulation, and digital familiarity impact both engagement and response, which could not be completely accounted for by statistical adjustment.

There are significant variations in the type of training data used, personalization algorithms, safety mechanisms and human oversight used by AI systems. Finally, sustainability is an outstanding unresolved topic as continued user engagement, technical maintenance, clinical governance and value within healthcare systems are required for long-term implementation (Espino Carrasco et al., 2025). Larger, more varied, and longer-term longitudinal studies, external validation, clinically diagnosed cohorts, direct comparisons with clinician-led interventions, and independent safety, fairness, and algorithmic performance assessments should be a priority in future research. Together this evidence will be needed to understand if the benefits of AI personalization can be sustained in real-world clinical practice and realized in safe, equitable, and clinically impactful mental health care.

CONCLUSION

Based on the findings of this study, AI-driven personalization could be a valuable tool for making digital mental health interventions more effective, leading to better psychological outcomes and increased engagement. When compared to standardized digital support, personalized intervention was found to be correlated with larger improvements in depression, anxiety, perceived stress and psychological well-being, and higher levels of personalization were correlated with higher levels of participation and self-monitoring. The results indicate that the benefits of AI in mental healthcare could go beyond automation to adapting the content, intensity, and timing of interventions based on the unique needs of each person. But customization does not mean that it should replace professional mental health care, especially for those who suffer from severe or worsening symptoms. To achieve clinical real-world use of personalized AI, it needs to be validated, evaluated over time, explainable, protected from sensitive behaviour and

fair, and clearly supervised by human beings. Further studies are needed to assess if these benefits continue to be applicable in larger, clinically more diverse, more culturally diverse patient populations, and in typical real-world healthcare settings.

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