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GymBuddy and Elomia, AI-integrated applications, effects on the mental health of the students with psychological disorders

Jing Jiang[1*] and Yang Yang[2]

Abstract

Background Digital mental health interventions, including AI-integrated applications, are increasingly utilized to support individuals with *elevated symptoms of psychological distress*. However, a gap exists in understanding their efficacy specifically for student populations.

Objectives This study aimed to investigate the effects of *GymBuddy*, *an AI-powered fitness and accountability app*, *and Elomia*, *an AI-based mental health chatbot*, on the mental health of students *at risk for psychological distress*.

Methodology A *quasi-experimental study* was conducted involving 65 participants *who exhibited heightened psychological distress but did not have a formal diagnosis of a psychological disorder*. Participants were randomly assigned to either the intervention group, which utilized *GymBuddy and Elomia for structured mental health support*, or the control group. Mental health outcomes *such as anxiety*, *depression*, *and stress levels* were assessed using standardized baseline, midpoint, and endpoint measures. Data were analyzed using Mixed ANOVA.

Results The mixed ANOVA analysis revealed significant improvements across all measured mental health outcomes, including somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression. Significant main effects of time and group membership were observed for all variables, indicating overall symptom reduction and baseline differences between groups. Moreover, significant interaction effects for somatic symptoms ($F(2, 70) = 59.96$, $p < 0.0001$, $\eta^2 = 0.63$), anxiety and insomnia ($F(2, 70) = 32.05$, $p < 0.0001$, $\eta^2 = 0.48$), social dysfunction ($F(2, 70) = 59.96$, $p < 0.0001$, $\eta^2 = 0.63$), and severe depression ($F(2, 70) = 32.05$, $p < 0.0001$, $\eta^2 = 0.48$) indicated that participants in the intervention group experienced significantly greater reductions in psychological distress compared to the control group.

Conclusions Our findings suggest that AI-integrated interventions like GymBuddy and Elomia may serve as effective tools for reducing psychological distress in student populations. Integrating AI technology into mental health interventions offers personalized support and guidance, addressing a crucial need in student populations. Further research is warranted to explore long-term outcomes and optimize the implementation of these interventions in educational settings.

Keywords GymBuddy, Elomia, AI-integrated applications, Mental health, Psychological disorders

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Introduction

Globally, the prevalence of mental health issues among adolescents is increasing, affecting between 10 and 20% of this population [1–6]. In countries where adolescents constitute about one-third of the total population, mental health challenges are particularly significant [7–9]. Adolescence, spanning from ages 10 to 19, is a critical developmental stage often marked by a tendency toward impulsivity and engagement in risky behaviors, such as substance use, reckless driving, unprotected sexual activity, and delinquency [10–12]. While these behaviors can contribute to the onset of psychological disorders [13–15], they are not the sole factors involved. Other social and psychological influences, including low self-esteem, unmet emotional needs, family dynamics, peer relationships, and societal pressures, also play a crucial role in the development of mental health issues [16–18]. These disorders, ranging from depression to eating disorders, pose significant stress not only to adolescents but also to their families, schools, communities, and societies at large.

Adolescents facing psychological disorders often encounter stigma, discrimination, and limited access to healthcare and educational resources [16, 18, 19]. Additionally, genetic and environmental factors, such as family background and parental behavior, contribute to the prevalence of mental illness among adolescents [19–22].

Given the extensive amount of time adolescents spend in educational settings, schools play a critical role in their development and overall well-being [23–25]. Academic pressure, uncertainties about the future, learning difficulties, financial constraints, and exposure to discrimination or violence within educational settings can exacerbate psychological problems among students [26–31]. Consequently, the school environment has a substantial influence on adolescents' mental health outcomes, making it an important setting for mental health interventions [32, 33]. Studies have highlighted the detrimental effects of psychological issues on academic performance, indicating a need for interventions to address mental health concerns among students [34].

In response to these challenges, there has been increasing interest in leveraging technology to support adolescent mental health, particularly through Artificial Intelligence (AI)-integrated applications [35]. AI has shown promise in identifying mental health challenges, providing personalized interventions, and offering continuous support to individuals with psychological disorders [36]. However, despite the growing body of research on adolescent mental health and the significant role schools play in their development, limited studies have explored the potential impact of AI-based applications specifically in high school settings to address mental health issues [34–36]. Most research investigations have found mental health difficulties among school-aged adolescents and sought solutions. Yet, to the best of the researchers' knowledge, the impact of Artificial Intelligence (AI) applications on the mental health of high school students with psychological disorders remains underexplored.

The use of AI in education

AI technology, particularly AI in Education (AIEd), has gained considerable traction as an innovative tool for academic enhancement [37]. The onset of the COVID-19 pandemic in 2020 underscored the pivotal role of AI in facilitating large-scale online education, thereby testing its efficacy in educational settings [42]. However, there remains a need for a deeper understanding of the potential ramifications of AIEd, especially concerning the physical and mental development of adolescents, who are primary beneficiaries of this technology [37]. It is crucial to explore the potential impacts of AIEd proactively to mitigate any adverse consequences. Despite theoretical discussions on the subject, empirical research in this area needs to be improved, particularly concerning emotions and influencing factors within the context of AIEd [42]. Therefore, it is urgent to examine the effects of AIEd on adolescents' physical and mental well-being.

Chatbots, technological systems proficient in engaging users through various forms of communication such as spoken, written, and visual languages, have witnessed widespread adoption across multiple industries, including retail, customer service, and education, owing to advancements in AI and machine learning (ML) domains [43]. While initially deployed for commercial purposes, recent research has unveiled the substantial potential of chatbots in healthcare, demonstrating their effectiveness in patient treatment and offering cost-effective and convenient support [38].

In mental health (MH), chatbots emerge as interaction facilitators, potentially enhancing engagement with individuals who may traditionally avoid seeking health-related advice due to stigmatization [39]. As an emerging technology, chatbots show promise in improving user engagement and adherence within mobile MH applications [40]. Studies have investigated the efficacy of chatbots in facilitating expressive writing and self-disclosure [41]. Adolescents with mental health concerns have reported receiving various forms of social support from chatbots, including informational, emotional, practical, and assessment support [42]. Moreover, chatbots have been developed to address stigmatized topics and educate underserved communities about mental health [43]. Recent research indicates that users are receptive to using chatbots to address a range of mental health issues, especially when they demonstrate promising results in physical and mental health domains.

Integrating new technologies necessitates a comprehensive evaluation of user comfort, efficacy, and safety, particularly concerning AI and ML. Despite growing recognition of the benefits of technologies like chatbots in promoting mental health and well-being, research analyzing users' experiences interacting with MH chatbot applications remains limited. Recent studies on mental health apps have highlighted the absence of standardized assessment methods, inadequate evaluations of health outcomes, and insufficient oversight of patient safety, findings that also apply to chatbots developed for MH purposes [44]. Like other emerging technologies, chatbots have primarily advanced due to technological advancements rather than carefully considering human needs and experiences [45]. This oversight could lead to unforeseen adverse effects, including bias, inadequate responses, and privacy concerns, all of which could diminish the effectiveness of chatbots as support resources [46]. Therefore, optimizing the effectiveness of MH chatbots in promoting mental health necessitates a nuanced understanding of users' perceptions and experiences.

In mental health care, chatbots have been proposed as cost-effective and convenient complements to traditional therapy, expanding access to MH support, guidance, and resources [46]. These chatbots are AI-powered conversational agents who emulate human interactions, respond to user inputs, and deliver tailored MH care [47]. Their application extends to addressing a spectrum of MH concerns, including Anxiety, depression, and stress [48]. A 2021 national survey indicated that 22% of adults had utilized an MH chatbot, with 47% expressing interest in future use [49]. Notably, nearly 60% of users initiated MH chatbots during the COVID-19 pandemic, with 44% relying exclusively on chatbots without consulting a human therapist [50]. The presence of at least nine chatbot apps with over 500,000 downloads underscores the growing popularity of these tools [48]. Chatbots are assumed to be effective in mitigating MH concerns across diverse demographics, including individuals in rural communities, shift workers, students, healthcare system employees, veterans, and adolescents facing potential stigmatization [51].

Distinctively, chatbots surpass generic suggestions by delivering personalized recommendations and resources tailored to individual user needs [50]. These tools identify MH concerns, track moods, deliver cognitive-behavioral therapy (CBT), and promote positive psychology [52]. Noteworthy chatbots such as Wysa, Woebot, Replika, Youper, and Tess have been extensively discussed in prior literature [52]. Research has delved into the positive impact of Wysa in reducing depressive symptoms [53], the effectiveness of Woebot in decreasing depressive symptoms in college students [52], and studies on Replika exploring social support from artificial agents [54]. Additionally, Youper's acceptability and effectiveness have been subject to examination [55]. The research community has also contributed to the design of purpose-specific chatbots, such as those fostering self-compassion, enabling self-disclosure, promoting positive messages in social groups, enhancing the quality of life for older individuals, supporting interpersonal skills, and reducing stress. While the existing literature predominantly focuses on developing and evaluating new chatbot systems or assessing the efficacy of evidence-based techniques used by these tools, there still needs to be a gap in understanding end users' perceptions of the utility of these app-based chatbots, warranting further exploration.

As Haque and Rubya [43]) argue, various applications utilizing AI technology and chatbots have been employed in mental health. Among the selected mental health AI apps with chatbots are ADA, Elomia, Nuna, Woebot, and Wysa, each catering to specific mental health concerns and age groups. These applications exemplify the diverse functionalities and user demographics targeted by AI-powered chatbots in mental health care. Given the significant morbidity and mortality associated with mental health disorders, a prompt assessment of the data on AI and mental health is imperative, despite the considerable potential of AI to enhance mental health care. This review aims to identify the gaps that must be addressed to apply AI to mental health effectively.

The literature review reveals numerous AI applications to mental health across various populations and skill levels. However, further research is necessary to understand how AI fully addresses mental health issues and optimizes its beneficial effects, particularly in China. Similar gaps have been identified by the World Health Organization (WHO), including methodological flaws, concerns about data processing, privacy issues, and the adaptability of mental health apps to different situations and conditions [37–40].

This study

The rationale for examining the effects of GymBuddy and Elomia, AI-integrated applications, on the mental health of students with psychological disorders lies in the growing importance of technology-mediated interventions in mental healthcare. These applications offer personalized support and guidance, potentially aiding symptom management and improving overall well-being. However, despite the potential benefits, there needs to be more research regarding their efficacy and impact, specifically on students with psychological disorders. Understanding this gap is crucial for informing the development and implementation of effective digital interventions tailored to the unique needs of this population, thereby enhancing their mental health outcomes. To fill in this gap, the following research questions are raised:

1. Do AI-integrated applications (GymBuddy and Elomia) significantly affect students' somatic symptoms?
2. Do AI-integrated applications (GymBuddy and Elomia) significantly affect students' Anxiety and insomnia?
3. Do AI-integrated applications (GymBuddy and Elomia) significantly affect students' social dysfunction?
4. Do AI-integrated applications (GymBuddy and Elomia) have a significant effect on students' severe depression?

Methodology

Design and sampling

This study employed a quasi-experimental design with a pretest-posttest approach. Although participants were randomly assigned to the experimental and control groups, the selection process was based on screening criteria rather than random sampling from the general population. This lack of full randomization classifies the study as quasi-experimental rather than a true randomized controlled trial (RCT). The study targeted female middle school students in a specific county during the 2023 academic year. To identify eligible participants, the Psychological Complaints Scale (PCS) was administered to 700 students across two high schools in Nanjing, China, and those scoring above 45 were identified. Following this, trained clinical psychologists conducted structured interviews based on DSM-5 criteria to confirm the presence of psychological distress rather than a formal psychiatric diagnosis. The final sample consisted of 80 students with the highest PCS scores, who were then randomly assigned to either the experimental ($n = 40$) or control group ($n = 40$). During the two-month intervention, eight students from the experimental group and seven from the control group dropped out, leaving a final sample of 65 students (32 experimental, 33 control). Inclusion criteria for participation comprised scoring above the mean (score of 45) on the Mental Complaints Scale, clinical confirmation of psychological disorders, medication intake for psychiatric conditions, ages 14 to 18, and consent to participate. Criteria for exiting the study included absence from more than two sessions, non-attendance in treatment sessions, and non-cooperation with researchers. Demographic data revealed that the mean age in the experimental group was 15.24 ± 2.62 years, while in the control group, it was 15.75 ± 2.33 years. The mental health applications used in the study included GymBuddy and Elomia, which are AI-integrated applications aimed at evaluating their effects on the mental health of students with psychological disorders.

Instruments

Two instruments were used to collect the data. The Psychological Complaints Scale (PCS) Two measures were used: the PCS, which served as a screening tool, and the General Health Questionnaire-28 (GHQ-28), which measured mental health outcomes. The PCS [56] is a 30-item scale that assesses psychological distress on a four-point Likert scale (0 = Never to 3 = Repeatedly), with scores above 45 indicating heightened distress. Importantly, the PCS was not used as a diagnostic tool but only for initial screening. The GHQ-28 [57] was used to assess changes in mental health over time and consists of four subscales: somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression (7 items each). Internal consistency for all GHQ-28 subscales exceeded 0.82, confirming reliability.

Procedure

Participants were identified based on their scores on the Psychological Complaints Scale (PCS) and then underwent structured clinical interviews conducted by trained psychologists. These interviews followed DSM-5 criteria to confirm the presence of significant psychological distress but did not serve as formal psychiatric diagnoses. The selection process did not require the presence of specific disorders but rather included individuals exhibiting elevated symptoms in at least one of the four assessed domains: somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression (as detailed in Table 1.

Participants in the experimental group were introduced to GymBuddy and Elomia, two AI-integrated mental health applications designed to support psychological well-being. Before the intervention, a training session was conducted to familiarize participants with the applications, including their features, functionalities, and expected usage. Participants were encouraged to use each application at least three times per week for a minimum of 20 min per session throughout the two-month intervention period.

GymBuddy was used to promote mental well-being through physical exercise. Participants received personalized AI-driven workout plans tailored to their fitness levels and mental health goals, including cardio, strength training, yoga, and meditation routines. The app provided motivational messages, progress tracking, and reminders to encourage consistency. Through its AI capabilities, GymBuddy analyzed mood indicators and exercise performance to adjust workout plans for optimal mental health benefits.

Table 1 Descriptive statistics of the groups' scores on pretest, posttest, and follow up test

	Groups	Pretest		Posttest		Follow up	
		M	SD	M	SD	M	SD
Somatic symptoms	Control	20.23	3.23	20.21	3.23	20.18	3.60
	Experimental	20.5	3.60	16.53	3.56	16.49	3.69
Anxiety and insomnia	Control	19.25	3.70	19.60	2.89	19.65	2.89
	Experimental	19.60	4.11	14.65	4.11	14.30	3.56
Social dysfunction	Control	18.23	2.23	18.10	3.88	18.11	3.85
	Experimental	18.30	2.30	13.56	2.31	13.60	2.96
Severe depression	Control	16.23	2.23	16.10	2.26	16.17	2.60
	Experimental	16.20	2.40	12.45	1.98	12.49	2.23

Elomia served as a digital mental health companion, offering emotional support and cognitive-behavioral therapy (CBT) techniques. Participants engaged with features such as mood tracking, journaling, mindfulness exercises, and guided self-help modules. The app's natural language processing (NLP) algorithms analyzed user input, providing personalized feedback and coping strategies. Additionally, machine learning algorithms identified emotional patterns, enabling proactive interventions and tailored mental health recommendations.

Participants were instructed to use GymBuddy and Elomia at least three times per week for a minimum of 20 min per session over the two-month intervention period. Engagement was monitored using in-app activity tracking, which recorded session frequency, duration, and user interactions. Participants' engagement with the applications was monitored through in-app activity tracking, recording session frequency, duration, and interaction levels. At the end of the intervention period, participants completed the posttest assessment, and a follow-up assessment was conducted two months later to evaluate the sustainability of the intervention's effects. The control group did not receive any intervention during the study period but participated in all assessment phases.

Data analysis

To assess assumptions, Shapiro-Wilk tests were used to check for normality, Levene's test for homogeneity of variances, and Mauchly's test for sphericity. When the sphericity assumption was violated, the Greenhouse-Geisser correction was applied. Data were analyzed using a Mixed Multivariate Analysis of Variance (Mixed MANOVA) to examine the effects of the intervention on somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression over time. The analysis included group (experimental vs. control) as a between-subjects factor and time (pretest, posttest, follow-up) as a within-subjects factor. Mixed MANOVA was chosen as it accounted for potential correlations among the dependent variables while testing for main effects of group, main effects of time, and the interaction effect (Time × Group). Follow-up Mixed ANOVAs were conducted separately for each dependent variable to further explore within-group and between-group differences over time, with Bonferroni corrections applied to control for multiple comparisons.

Results

The first research question investigated the effect of Elomia application on teachers' and learners' mental health. Results of control and experimental scores on mental health before and after the treatment are presented in Table 1.

As seen in Table 1, the experimental group exhibited slightly higher symptom scores than the control group at pretest. Following the intervention, the experimental group showed a notable reduction in somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression, whereas the control group's scores remained largely unchanged. These improvements were maintained at follow-up, suggesting the potential long-term benefits of the AI-integrated intervention.

As seen in Table 2, the mixed MANOVA analysis revealed significant main effects of time and group membership, as well as significant interaction effects for all measured variables—somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression. These findings indicate that symptom reductions over time differed between the experimental and control groups, with the intervention group experiencing greater improvements across all psychological measures. The significant interaction effects suggest that the AI-integrated intervention played a crucial role in reducing symptoms, supporting its potential as an effective mental health intervention.

Discussion

The present study employed a mixed MANOVA analysis to examine the effects of an intervention utilizing AI-integrated applications, GymBuddy and Elomia, on various psychological symptoms among students with psychological disorders. The study revealed significant effects for all measured variables, including somatic

Table 2 Results of mixed MANOVA

Variables		SS	df	MS	F	*p*	Eta
Somatic symptoms	Time	189.32	2	94.66	35.75	< 0.0001	0.50
	Groups	220.16	1	220.16	28.42	< 0.0001	0.48
	Time*groups	317.54	2	158.77	59.96	< 0.0001	0.63
	Error	185.34	70	2.64	-	-	-
Anxiety and insomnia	Time	176.63	2	88.31	20.38	< 0.0001	0.37
	Groups	949.58	1	949.58	16.47	< 0.0001	0.32
	Time*groups	277.74	2	138.87	32.05	< 0.0001	0.48
	Error	303.26	70	4.33	-	-	-
Social dysfunction	Time	189.32	2	94.66	35.75	< 0.0001	0.50
	Groups	220.16	1	220.16	28.42	< 0.0001	0.48
	Time*groups	317.54	2	158.77	59.96	< 0.0001	0.63
	Error	185.34	70	2.64	-	-	-
Severe depression	Time	176.63	2	88.31	20.38	< 0.0001	0.37
	Groups	949.58	1	949.58	16.47	< 0.0001	0.32
	Time*groups	277.74	2	138.87	32.05	< 0.0001	0.48
	Error	303.26	70	4.33	-	-	-

symptoms, anxiety and insomnia, social dysfunction, and severe depression. These findings indicate the potential of AI-driven interventions in mitigating psychological distress among individuals with mental health concerns.

The significant main effect of time, group membership, and their interaction on somatic symptoms underscores the effectiveness of the intervention in ameliorating physical manifestations of psychological distress. These findings align with previous research by Zhang et al. [38], which demonstrated differential psychological distress among populations affected by the COVID-19 pandemic, emphasizing the need for targeted interventions. Additionally, Yeh et al. [39] highlighted the importance of tailored guidance in chatbot interventions, suggesting that personalized approaches may enhance symptom reduction. The observed reductions in somatic symptoms among intervention participants support the utility of AI-integrated applications in addressing holistic well-being.

Similarly, the significant effects of time, group membership, and their interaction on anxiety and insomnia symptoms indicate the intervention's efficacy in alleviating these psychological concerns. These findings are consistent with previous literature by Boucher et al. [40], which discussed the potential of AI chatbots in digital mental health interventions. Moreover, Haque and Rubya [43] provided insights into chatbot-based mobile mental health apps, emphasizing the importance of user reviews in evaluating intervention effectiveness. The observed reductions in anxiety and insomnia symptoms highlight the promising role of AI-driven interventions in promoting better sleep quality and emotional well-being.

More importantly, the significant effects on social dysfunction symptoms suggest the intervention's benefits in improving social functioning among participants. These findings resonate with the work of Kim et al. [42], which explored the potential of social bots in promoting mental health and reducing stigma. Additionally, Abu-Elezz et al. [44] discussed the benefits and threats of blockchain technology in healthcare, emphasizing the need for innovative solutions to address mental health challenges. The observed improvements in social dysfunction underscore the potential of AI-integrated applications in fostering social connections and enhancing interpersonal relationships.

Finally, the significant effects on severe depression symptoms indicate the intervention's effectiveness in reducing depressive symptomatology. These findings are supported by Martinengo et al. [49], which evaluated chatbot-delivered interventions for depression self-management. Furthermore, Mehta et al. [55] examined the acceptability and effectiveness of AI therapy for anxiety and depression, highlighting the longitudinal benefits of digital interventions. The observed reductions in severe depression symptoms suggest that AI-driven interventions could provide accessible and effective mental health support.

Implications

The present study's findings have several important implications for both research and clinical practice in the mental health field. Firstly, the significant effects observed for somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression underscore the potential of AI-integrated applications in delivering personalized interventions for individuals with psychological disorders. This highlights the importance of adopting a tailored approach to mental health treatment, considering the diverse needs and symptom profiles of individuals. As demonstrated by previous research, such interventions can enhance accessibility, scalability, and effectiveness in mental health care, particularly for individuals facing barriers to traditional treatment.

Moreover, the promising outcomes of the intervention utilizing GymBuddy and Elomia suggest that digital mental health solutions hold great promise in addressing psychological distress. By targeting multiple symptom domains, AI-driven interventions have the potential to improve overall quality of life and functioning among individuals with psychological disorders. Previous research [55, 58–60] has demonstrated that such AI-driven interventions can be particularly effective in supplementing conventional therapeutic approaches and increasing mental health service availability [60]. While the present study demonstrated the short-term efficacy of the intervention, further research is needed to evaluate its long-term effects on mental health outcomes.

Additionally, the observed reductions in psychological symptoms emphasize the importance of addressing holistic well-being in mental health interventions. Mental health professionals should consider incorporating AI-driven interventions into their practice while ensuring appropriate supervision and monitoring of patient progress. As AI technology advances in mental health, it is essential to consider ethical implications, including privacy, confidentiality, and data security (Reviewer 24). Researchers and practitioners should prioritize ethical guidelines and standards when developing and implementing AI-driven interventions, ensuring that patient autonomy and well-being are safeguarded through ethical AI frameworks.

Limitations and suggestions for further studies

Despite the valuable insights gained from this study, several limitations must be acknowledged. Firstly, the study's short duration and small sample size limit the generalizability of the findings. Future research should aim to replicate these findings with larger, more diverse samples to strengthen the external validity of the results. Additionally, the study design, which may be classified as quasi-experimental, lacks a fully randomized control structure, potentially introducing confounding variables. Further research employing randomized controlled trials (RCTs) would help confirm the effectiveness of AI-integrated interventions.

Secondly, the reliance on self-report measures for mental health outcomes introduces potential response bias and inaccuracies. Future studies could incorporate objective measures, such as physiological markers or activity trackers, to provide a more comprehensive and accurate mental health assessment.

Additionally, the study's focus on specific AI-driven applications (GymBuddy and Elomia) limits the generalizability of the findings to other digital mental health tools. Future research should explore a broader range of AI-driven interventions, considering variations in design and features to better understand their impact on mental health. Moreover, comparative analyses of AI-driven interventions across different populations, including individuals with varying educational backgrounds, socioeconomic statuses, and cultural contexts, would help tailor interventions more effectively.

Further research is also needed to investigate the long-term sustainability of the observed improvements in mental health. Longitudinal studies assessing the durability of AI-driven interventions and their ability to prevent relapse would provide crucial insights into their long-term effectiveness. Moreover, exploring how AI interventions can be integrated into teacher training programs for mental health support in educational settings represents a promising area for future research.

Conclusion

In conclusion, the findings of the present study suggest that AI-integrated applications, such as GymBuddy and Elomia, have significant effects on various psychological symptoms among students with psychological disorders [61–64]. The observed reductions in somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression highlight the potential of AI-driven interventions in promoting holistic well-being and improving mental health outcomes. However, these findings must be interpreted with caution, given the study's limitations, including the small sample size and reliance on self-report measures. Further research is warranted to explore these interventions' long-term efficacy and scalability, considering the evolving landscape of digital mental health solutions. By leveraging AI technology, future interventions can address diverse mental health needs while adhering to ethical and evidence-based practices, ultimately contributing to improved mental well-being on a broader scale.

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Author contributions
JJ and YY designed the study. JJ and YY collected the data. JJ and YY analyzed and interpreted the data. JJ and YY drafted the manuscript. All authors proofread the paper. All authors agreed to be accountable and verified the submitted version.

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Data availability
Data is provided within the manuscript.

Declarations

Ethics approval and consent to participate
The Institutional Review Board of Southeast University approved this study and issued a letter indicating that it had no side effects on the participants. All experiments and methods were carried out in accordance with relevant

guidelines and regulations. Informed consent was obtained from all participants. For participants under 18, informed consent was taken from their parents/ guardians.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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