Generative AI Empowering Personalized Intervention Models for College Student Mental Health Education

***Yanhua Zhong[1], Chunyan Zhong[2], Wen Wu[1], Yanping Chen[1]**

[1]School of Marxism, Ganzhou Polytechnic, Ganzhou, Jiangxi, 341000, China

[2]Shenzhen Longgang District Bantian Street Central Kindergarten, Shenzhen, Guangdong, 518000, China

***Corresponding Author**

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ABSTRACT

The increasing prevalence of mental health issues among college students has become a pressing concern for higher education institutions worldwide. Traditional mental health education models, characterized by one-size-fits-all curricula and reactive crisis intervention, often fail to address the diverse and dynamic needs of individual students. The emergence of Generative Artificial Intelligence (GAI) offers unprecedented opportunities for transforming mental health education from a standardized approach to a personalized, proactive, and scalable system. This study addresses the gap between the potential of GAI and its application in college mental health education by conceptualizing a personalized intervention model. Drawing on a synthesis of existing literature on mental health education, personalized learning, and AI-driven intervention, the study proposes a four-component model comprising: (1) multidimensional student profiling for personalized needs assessment; (2) GAI-powered personalized content generation; (3) adaptive intervention pathways with tiered support levels; and (4) continuous feedback loops for model optimization. The study further analyzes three core mechanisms through which GAI enables personalization: dynamic learner modeling, contextualized intervention design, and empathetic conversational interaction. The proposed model shifts the paradigm from reactive crisis management to proactive psychological nurturing, from group-based instruction to individualized support, and from human-only delivery to human-AI collaboration. Theoretically, this study contributes a systematic framework for understanding GAI applications in mental health education. Practically, it offers actionable guidance for educators, counselors, and policymakers seeking to leverage GAI for improving college student mental health outcomes. Future research should empirically validate the model through longitudinal interventions and examine its effectiveness across diverse student populations.

Keywords: Generative AI, personalized intervention, mental health education, college students, intervention model

INTRODUCTION

The mental health of college students has emerged as a critical concern for higher education institutions globally. Studies have documented rising rates of anxiety, depression, and psychological distress among young adults, with the college years representing a vulnerable period for the onset of mental health challenges (Eisenberg et al., 2022; Husky et al., 2023). In China, the situation is equally concerning, with recent surveys indicating that a significant proportion of college students experience moderate to severe psychological distress, exacerbated by academic pressure, career uncertainty, and social adjustment challenges (Wang & Zhang, 2024; Li et al., 2025).

Traditional mental health education in colleges and universities has relied on several conventional approaches. These include large-group lectures on psychological well-being, counseling services available on a drop-in or appointment basis, and crisis intervention protocols activated when students reach critical states. The

importance of reimagining mental health education cannot be overstated. Poor mental health not only impairs academic performance and quality of life but also poses risks to students' physical health and long-term development. In severe cases, untreated mental health issues may lead to self-harm or suicidal ideation, making effective intervention a matter of student safety. As the demand for mental health services continues to outpace the supply of professional counselors, finding scalable yet personalized solutions is an urgent practical necessity.

While these traditional approaches have value, they suffer from several inherent limitations. First, they are predominantly reactive rather than proactive, intervening only after problems become acute. Second, they offer standardized content that fails to address individual differences in psychological needs, cultural backgrounds, and personal circumstances. Third, they face significant scalability challenges, with campus counseling centers typically understaffed relative to student populations (Xiao et al., 2023). Fourth, many students hesitate to seek help due to stigma, privacy concerns, or lack of awareness, resulting in untreated deterioration (Cage et al., 2020; Hyseni Duraku et al., 2023)

The specific need addressed by this study is threefold. First, educators and counselors lack practical frameworks for integrating GAI into mental health education in ways that are both effective and ethical. Second, mental health education systems lack the infrastructure for delivering personalized interventions at scale. Third, the existing literature offers either technological descriptions of AI capabilities or clinical discussions of mental health interventions, with little integration of the two domains. This study directly responds to these needs by developing a personalized intervention model that bridges GAI technology with mental health education practice.

The emergence of Generative Artificial Intelligence (GAI), exemplified by large language models such as ChatGPT, DeepSeek, and ERNIE, offers transformative possibilities for addressing these limitations. Unlike traditional AI systems designed for classification or prediction, GAI can generate novel, contextually relevant content in response to user inputs. This capability opens new avenues for personalized mental health education. GAI can serve as a 24/7 accessible conversational agent, generate tailored psychoeducational content, simulate realistic scenarios for skills practice, and adapt interventions based on ongoing student interactions (Ray, 2023; Lu, 2025).

The relevance of this study extends to multiple beneficiaries. For students, the proposed model offers the possibility of timely, accessible, and personalized mental health support that respects individual differences and preferences. For counselors and mental health professionals, the model provides a framework for extending their reach through human-AI collaboration, allowing them to focus on complex cases while AI handles routine support and early intervention. For college administrators, the model offers a scalable solution to meet growing mental health demands without proportionally increasing staffing. For policymakers, the study informs guidelines for ethical AI integration in mental health services. Ultimately, the primary beneficiary is the student, who deserves effective, accessible, and personalized mental health support.

However, the application of GAI in mental health education is not without challenges. Concerns about data privacy, algorithmic bias, diagnostic accuracy, and the appropriateness of AI-delivered emotional support must be carefully addressed. Floridi (2019) has argued that digital ethics must move from principles to practices, embedding ethical requirements into technical design. This insight is particularly relevant for mental health applications, where the stakes for misuse or error are exceptionally high.

The current literature has established the potential of AI in mental health, including chatbot-based interventions (Fitzpatrick et al., 2017), predictive models for suicide risk (Seyedsaleh & Faze, 2024), and natural language processing for symptom assessment (Zhang et al., 2022). However, a critical gap remains. Most existing studies focus on specific AI applications (e.g., a particular chatbot for depression) or narrow aspects of personalization. What is missing is an integrated, systematic model of personalized intervention that specifies how GAI can be deployed across the continuum of mental health education from universal prevention to targeted intervention to intensive support. This study addresses this gap by developing a comprehensive personalized intervention model grounded in educational and psychological theory. As Selwyn (2019) has observed in the broader context of educational technology, successful integration requires not only technical

understanding but also pedagogical and ethical frameworks. This study provides such a framework for the domain of mental health education.

This study addresses the identified gap by proposing a personalized intervention model for GAI in college student mental health education. Specifically, it conceptualizes how GAI can enable four core components of personalization: student profiling for needs assessment, personalized content generation, adaptive intervention pathways, and continuous feedback optimization. The study further analyzes the mechanisms through which GAI achieves personalization and discusses the implications for practice, policy, and future research.

The research poses three questions: (1) What components constitute a personalized intervention model for GAI in mental health education? (2) Through what mechanisms does GAI enable personalization in this context? (3) How can such a model be implemented effectively and ethically in college settings?

The remainder of this paper is structured as follows. Section 2 reviews the existing literature on mental health education challenges, personalized learning, and AI applications in mental health. Section 3 presents the theoretical framework underpinning the proposed model. Section 4 develops the personalized intervention model in detail, specifying its components and mechanisms. Section 5 discusses the implications for practice, policy, and future research. Section 6 concludes with limitations and conclusions.

LITERATURE REVIEW

Mental Health Education for College Students: Challenges and Limitations

Mental health education in higher education encompasses a range of activities designed to promote psychological well-being, prevent mental disorders, and provide early intervention for students experiencing distress (Barros, 2025). In Chinese universities, mental health education has become a mandated component of the curriculum, with most institutions offering courses on psychological adjustment, stress management, and interpersonal relationships.

Despite these efforts, significant challenges persist. First, the student-to-counselor ratio at most Chinese universities far exceeds recommended levels. While international guidelines suggest one counselor per 1,000 to 1,500 students, ratios of 1:3,000 or higher are common in Chinese institutions (Xiao et al., 2023). This shortage severely limits the availability of individualized support.

Second, stigma and help-seeking barriers prevent many students from accessing available services. Research indicates that college students frequently underestimate the severity of their own distress, fear judgment from peers, or doubt the effectiveness of counseling (Cage et al., 2020; Li et al., 2024). The result is that many students who could benefit from intervention never seek it.

Third, one-size-fits-all curricula fail to address the heterogeneity of student needs. Mental health challenges vary considerably across student populations, with factors such as gender, academic major, family background, and prior trauma history all influencing psychological profiles (Allen, 2025; Eisenberg et al., 2022). Standardized curricula delivered through large lectures cannot accommodate this diversity.

Fourth, mental health education remains largely reactive, activating only after problems have become apparent rather than preventing their emergence. The absence of continuous monitoring and early warning systems means that early signs of distress often go unnoticed until they escalate into crises.

Personalized Learning and Adaptive Interventions

Personalized learning has emerged as a prominent paradigm in educational research, emphasizing the tailoring of instruction to individual learner characteristics, preferences, and needs. The core premise is that learning is more effective when content, pace, and modality align with the learner's profile (Pane et al., 2015).

In the context of mental health education, personalization is particularly critical. Students vary not only in their baseline psychological status but also in their preferred coping styles, cultural assumptions about mental health, and readiness for change (Hall et al., 2021). A personalized approach respects this diversity and can adapt interventions to match individual readiness and circumstances.

Adaptive intervention designs, also known as just-in-time adaptive interventions (JITAI), represent an advanced form of personalization that adjusts support based on real-time or near-real-time assessments of user state (Kantharaju et al., 2023). These designs have been successfully applied in health behavior change contexts, such as smoking cessation and physical activity promotion. However, their application in mental health education, particularly using GAI, remains underdeveloped.

Generative AI in Mental Health: Current Applications

The application of AI in mental health has grown rapidly. Early work focused on rule-based chatbots designed to deliver cognitive-behavioral therapy (CBT) principles. Woebot, a prominent example, demonstrated that chatbot-delivered CBT could significantly reduce depression and anxiety symptoms in college students (Fitzpatrick et al., 2017).

More recently, the emergence of large language models has expanded possibilities. GAI systems can engage in open-ended conversation, generate personalized psychoeducational content, and simulate therapeutic dialogue. Preliminary studies suggest that students find AI-based mental health tools acceptable, with some reporting authentic therapeutic alliance with chatbots (Darcy et al., 2021). However, the current literature has significant gaps. Studies have focused primarily on AI as a tool for delivering established therapeutic protocols, not as an enabler of dynamic personalization. Few studies have systematically addressed how GAI can adapt interventions to individual student profiles, circumstances, and progress. Moreover, the integration of GAI into mental health education curricula, as distinct from clinical counseling, has received limited attention. This study addresses these gaps by developing a personalized intervention model specifically designed for educational contexts.

Research Gap and Contribution of This Study

The literature review reveals a clear research gap. Existing studies have established the potential of AI in mental health and recognized the importance of personalization, but they have not developed an integrated model of personalized GAI intervention for college mental health education. Consequently, educators lack frameworks for implementation, and researchers lack theoretical foundations for hypothesis testing.

This study addresses this gap by proposing a comprehensive personalized intervention model. The contribution is twofold. Theoretically, the study synthesizes insights from mental health education, personalized learning, and AI to develop a systematic framework for personalization. Practically, the model provides actionable guidance for implementing GAI-based personalized interventions in college settings.

THEORETICAL FRAMEWORK

The proposed model draws on three theoretical foundations: the tiered model of intervention, personalized learning theory, and human-AI collaboration frameworks.

Tiered Model of Intervention

The tiered model, widely used in mental health and special education, organizes interventions into levels of increasing intensity. Level 1 (universal) applies to all students and focuses on prevention and wellness promotion. Level 2 (targeted) addresses students identified as at-risk through standardized screening. Level 3 (intensive) provides individualized support for students with diagnosed conditions or severe distress.

GAI can support all three levels. For universal prevention, GAI can deliver psychoeducational content and wellness tips to entire student populations. For targeted intervention, GAI can provide personalized support

based on screening results. For intensive support, GAI can augment counselor-delivered therapy by providing between-session reinforcement and skill practice.

Personalized Learning Theory

Personalized learning theory emphasizes the adaptation of instruction to individual learner characteristics. Key dimensions include content personalization (what is taught), pacing personalization (how fast), modality personalization (through what medium), and goal personalization (what outcomes matter).

GAI enables personalization along all dimensions. It can generate customized content based on individual profiles, adapt difficulty dynamically, deliver through preferred modalities, and align with personal goals.

Human-AI Collaboration

The concept of human-AI collaboration recognizes that AI is not intended to replace human professionals but to augment their capabilities. In mental health, this collaboration can take several forms: AI can handle routine support and triage, freeing counselors for complex cases; AI can provide continuous monitoring and early warning, enabling timely human intervention; and AI can offer between-session support, extending the reach of professional services.

A PERSONALIZED INTERVENTION MODEL FOR GAI IN MENTAL HEALTH EDUCATION

This section presents the proposed personalized intervention model. The model consists of four interconnected components and three core mechanisms.

Model Components

Component 1: Multidimensional Student Profiling

The foundation of personalization is accurate profiling of student characteristics. The proposed model includes four profiling dimensions. The four profiling dimensions are summarized in Table 1 below.

Table 1. Dimensions of Multidimensional Student Profiling

Dimension	Description	Data Sources
Psychological status	Current mental health state, risk level	Screening questionnaires, self-report
Learning preferences	Preferred modalities, pace, and content types	Behavioral data, surveys
Personal context	Academic pressure, social support, life events	Registration data, self-report
Intervention history	Past engagement, response patterns	System logs, counselor notes

GAI can integrate these diverse data sources to construct comprehensive student profiles, identify patterns that humans might miss, and update profiles dynamically as new data become available.

Component 2: GAI-Powered Personalized Content Generation

Using student profiles, GAI generates personalized intervention content. This includes:

- Psychoeducational materials tailored to individual knowledge gaps and learning preferences
- Skill-building exercises customized to student-identified challenges

- Reflection prompts designed to address specific cognitive patterns
- Scenario-based simulations relevant to student life contexts

The personalization algorithm considers both student characteristics and evidence-based intervention principles.

Component 3: Adaptive Intervention Pathways with Tiered Support

The model organizes interventions along a tiered pathway. The tiered intervention pathway with corresponding GAI and human roles is presented in Table 2.

Table 2. Tiered Intervention Pathway with GAI and Human Roles

Tier	Target Population	GAI Role	Human Role
Tier 1 (Universal)	All students	Deliver wellness content, monitor engagement	Oversee quality, update content
Tier 2 (Targeted)	At-risk students	Provide personalized support, trigger alerts	Review cases, provide brief counseling
Tier 3 (Intensive)	High-need students	Reinforce skills, support between sessions	Deliver therapy, coordinate care

GAI continuously assesses student progress and recommends movement between tiers based on response patterns.

Component 4: Continuous Feedback and Model Optimization

The final component closes the loop between intervention and improvement. GAI collects data on student engagement, satisfaction, and outcomes; analyzes patterns to identify what works for whom; and updates personalization algorithms accordingly. This continuous learning ensures that interventions become more effective over time.

Core Mechanisms of Personalization

Mechanism 1: Dynamic Learner Modeling

GAI continuously updates student profiles based on new interactions. Unlike static assessments administered at intake, dynamic modeling captures changes in psychological state, learning progress, and life circumstances as they occur. This enables just-in-time personalization.

Mechanism 2: Contextualized Intervention Design

GAI generates interventions that reference student-specific contexts, such as academic deadlines, social situations, or personal goals. Contextualized interventions are more relevant and engaging than generic content.

Mechanism 3: Empathetic Conversational Interaction

GAI engages students in natural-language dialogue that simulates empathetic listening. Through careful prompt engineering and value alignment, GAI can provide supportive responses that acknowledge student emotions while guiding toward evidence-based coping strategies. The overall structure of the model is illustrated in Figure 1.

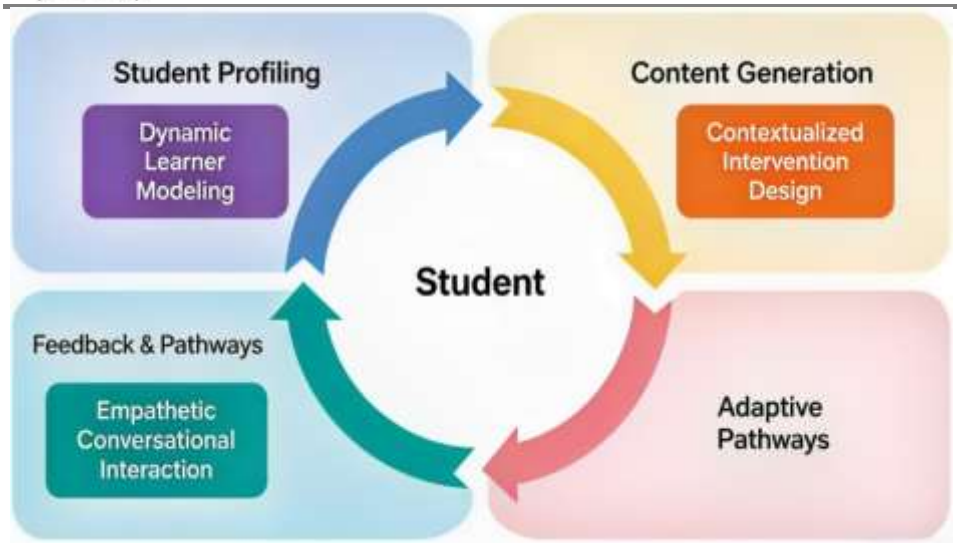

Figure 1. Personalized Intervention Model

The model consists of four cyclical components: multidimensional student profiling, GAI-powered personalized content generation, adaptive intervention pathways, and continuous feedback and model optimization, with the student at the center. Three core mechanisms enable personalization: dynamic learner modeling, contextualized intervention design, and empathetic conversational interaction. Table 3 provides a summary of the four model components, their key functions, GAI contributions, and implementation considerations.

Table 3. Summary of the Personalized Intervention Model

Component	**Key Function**	**GAI Contribution**	**Implementation Considerations**
Student profiling	Assess needs and characteristics	Integrate diverse data, update dynamically	Privacy protection, informed consent
Content generation	Produce personalized materials	Tailor to individual profiles	Factual accuracy, value alignment
Adaptive pathways	Match support level to need	Recommend tier movement, trigger alerts	Clear escalation protocols
Feedback optimization	Improve over time	Analyze patterns, update algorithms	Human oversight of changes

DISCUSSION

Theoretical Implications

The model contributes to theory in three ways. First, it extends personalized learning theory to mental health education, specifying how personalization principles apply in this domain. Second, it operationalizes the tiered intervention model for GAI-based delivery, addressing a gap in implementation frameworks. Third, it articulates mechanisms of GAI-enabled personalization, providing a foundation for empirical testing.

Practical Implications for Implementation

For educators and counselors, the model provides a roadmap for integrating GAI into mental health education. Key implementation considerations include:

• Start with universal prevention (Tier 1) to build experience and trust before expanding to targeted and intensive support.

• Maintain human oversight of AI-generated content, particularly for mental health information that could cause harm if inaccurate.

• Establish clear escalation protocols for identifying when human intervention is needed, with particular attention to crisis situations.

• Design for privacy and transparency, ensuring students understand how their data will be used and have control over their information.

For administrators and policymakers, the model suggests investments in technical infrastructure, training for counselors, and ethical guidelines for GAI use.

Evaluating Model Effectiveness

To bridge the gap between conceptualization and implementation, clear metrics for evaluating the model's effectiveness are essential. Future research and pilot applications should consider a mixed-methods evaluation framework, including: (1) engagement metrics (e.g., frequency and duration of student-GAI interactions, feature usage patterns); (2) outcome metrics (e.g., changes in standardized mental health screening scores, self-reported well-being, academic help-seeking behavior); and (3) process metrics (e.g., fidelity to the tiered pathway, accuracy of risk alerts, quality of human-AI collaboration). These metrics would allow for iterative refinement of the model based on empirical evidence.

Ethical Considerations

The application of GAI in mental health raises several ethical concerns. Beyond general ethical principles, specific risks require careful attention. GAI "hallucination," the generation of factually incorrect or nonsensical information, poses a significant danger in mental health contexts, where inaccurate advice could exacerbate a student's condition. The model requires robust data protection measures and transparent data use policies. Algorithmic bias could result in differential intervention quality across student populations, requiring careful validation across demographic groups. Appropriate boundaries must be maintained, with clear communication to students that GAI is a support tool, not a substitute for professional mental health treatment. Students in crisis must be directed to human counselors, not managed solely by AI.

Furthermore, the successful implementation of this model depends on adequate institutional infrastructure, technical training for counselors, and ongoing cost considerations. Over-reliance on GAI may also lead to reduced human interaction and a potential deskilling of basic counseling competencies among students. These risks do not undermine the model's validity but rather highlight the importance of careful, phased implementation with continuous human oversight. Floridi (2019) argues that digital ethics must move from principles to practices, embedding ethical requirements into technical design. This model incorporates these ethical considerations and risk awareness as integral design features.

Limitations and Future Research

This study has several limitations. First, the model is theoretical and has not been empirically validated. The proposed personalized intervention framework requires testing through pilot implementations to assess its feasibility, acceptability, and effectiveness in real-world settings. Second, the model does not specify technical requirements for implementation. Different GAI platforms, configurations, and integration architectures may yield varying results, necessitating further technical investigation. Third, the model focuses primarily on student-facing intervention, with limited attention to counselor support systems and institutional infrastructure. The successful deployment of GAI-based mental health education likely depends on these broader ecosystem factors. Future research should empirically validate the model through longitudinal intervention studies,

examine optimal human-AI collaboration models, and explore cultural adaptations for diverse student populations.

CONCLUSION

This study addressed the gap between the potential of Generative Artificial Intelligence and its application in college mental health education by proposing a personalized intervention model. Drawing on literature from mental health education, personalized learning, and AI, the study developed a four-component model comprising student profiling, personalized content generation, adaptive intervention pathways, and continuous feedback optimization. The study further identified three core mechanisms through which GAI enables personalization: dynamic learner modeling, contextualized intervention design, and empathetic conversational interaction.

The model shifts the paradigm for mental health education from reactive to proactive, from standardized to personalized, and from human-only to human-AI collaborative. Theoretically, the study contributes a systematic framework for understanding GAI in mental health education. Practically, it provides actionable guidance for educators, counselors, and policymakers seeking to leverage GAI for improving college student mental health outcomes.

The integration of GAI into mental health education is likely to accelerate as technologies mature. The question is not whether to adopt these technologies, but how to implement them effectively and ethically. This study has taken a first step by articulating a comprehensive personalized intervention model. Future research should empirically validate the model through longitudinal interventions, refine its components based on implementation experience, and develop ethical guidelines for responsible use. Ultimately, the goal is to harness GAI's capabilities to make quality mental health support accessible, personalized, and available to every student who needs it.

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