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REVIEW

The Impacts of AI on College Students' Mental Health and Well-Being in Higher Education System: A Systematic Review Approach

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ABSTRACT: Background: The role of artificial intelligence in influencing the mental health and well-being of students in higher education has become increasingly significant globally and locally. However, there is still a paucity of research that systematically investigates the effects of artificial intelligence on students' psychological health and well-being from a comprehensive perspective. **Methods:** Followed the Prisma 2020 guidelines, this study employs a systematic literature review to examine the impacts of artificial intelligence on college students' mental health and well-being in higher education contexts. Data were obtained from three major academic databases—Scopus, the (EBSCOhost) Research Databases, and the Social Sciences Citation Index (SSCI) via Web of Science, and 24 peer-reviewed publications were selected. Regarding the eligible research works included in this review, a comprehensive analysis and documentation were conducted on their core fundamental characteristics. Specifically, the key indicators under investigation encompassed the temporal trends of publication years, adopted research methodologies, affiliations corresponding to the first authors, specific AI tools evaluated in each study, and the geographical distribution of research contributions. **Results:** The findings indicate that the most represented regions include China, Saudi Arabia, Turkey, Jordan, Brunei, Peru, Palestine, Colombia, and the USA. Among all the included publications, China accounted for the largest volume of relevant studies, as 12 screened eligible works were conducted by researchers based in China. From a temporal perspective, the earliest relevant study was published in 2022, while the year 2025 witnessed the peak of publication output, with a total of 14 articles released in 2025. **Conclusion:** Artificial intelligence is associated with several negative psychological outcomes, including AI-induced anxiety, feelings of alienation, social isolation, loneliness, and stress, which have grown increasingly prevalent among university students. Conversely, AI also demonstrates positive contributions to psychological well-being through enhanced learning support, accessibility, and personalized mental health interventions.

KEYWORDS: Artificial intelligence; psychological well-being; systematic review; artificial intelligence in education (AIED); students' anxiety; loneliness

1 Introduction

With the advancement of artificial intelligence (AI), AI can influence the mental health and overall well-being of college students at both global and local levels [1–4]. The academic community is increasingly recognizing the significant educational value of deep connections between teachers and students. However, paradoxically, few have critically examined whether computer-mediated learning models are systematically diminishing the humanistic warmth within the campus environment [5]. In fact, a defining feature of contemporary society is the pervasive and enduring belief in the transformative power of technology [6]. This steadfast belief in technology may ultimately lead to the use of technology falling into the ethical paradox of "dual use".

Since the late 1990s, the "dual use bias" of beneficial scientific knowledge and technology has become a subject of scientific research, ethical concerns, and policy interventions [7]. "Dual use" generally describes the potential of a given technology or scientific research to be applied for both beneficial and harmful purposes, with research outcomes or technologies themselves not being the agents of misuse [8]. Epistemic and material products, such as research findings and technological artifacts, are inherently vulnerable to the risks posed by dual-use concerns [9], and AI is no exception. AI's integration into education can be considered a double-edged sword, providing advantages such as innovation and productivity, while also presenting challenges and drawbacks across various dimensions [10]. From the perspective of tool characteristics, the deployment of AI in postsecondary education can be conceptualized as a dual-use phenomenon in mental health as well, offering significant potential in the realm of mental health for early detection, personalized interventions, and increased accessibility, while simultaneously presenting potential challenges in terms of ethics, psychological dependence, and other related issues. Recently, research has shown that the prevalence of mental health issues among college students has increased over the past several years, due to factors like more and more pressure from schoolwork, socio-economic inequalities, and the expanding impact of AI [11].

The extensive integration of AI into tertiary education holds the potential to significantly enhance students' learning efficiency and academic performance. Generative AI's potential reaches far beyond essay writing, with tools like DeepL and Google Translate breaking down language barriers and enhancing access to academic resources, thereby fostering cross-cultural learning opportunities [12]. As AI technology advances, its growing potential for personalized and adaptive learning allows educators to design dynamic curricula and offer support that individual teachers alone could not provide [13]. And studies have shown that personalized learning content tailored to individual needs can improve the educational experience and yield better outcomes for international students [14]. Additionally, according to McGrath et al.' s study, AI-assisted support may be especially advantageous for students from vulnerable populations, including those with learning difficulties [15]. And some scholars contend that the adoption of AI technologies across higher education contexts could facilitate educational equity to some degree [15,16].

In terms of the large-scale application of AI and its implications for the mental health of university and college students, many studies in the field of educational psychology have been carried out, which are attracting worldwide scholars' attention to these studies [3,4,11]. Some scholars have noticed more worries about AI, especially AI chatbots, harming students' minds and feelings, at the same time as these things have become more popular dramatically quickly [17]. Furthermore, several scholars have also noted many adverse effects on students' psychological health introduced by AI. For example, Nakshine et al. pointed out that the increased screen exposure caused by using AI may bring negative effects, including digital fatigue [18], social isolation, heightened anxiety, and compromised mental well-being. Some studies showed that people might become overly reliant on or addicted to AI, like becoming attached to a chatbot, depending on a social chatbot, or counting on conversational AI [19–23]. Drawing on the technological dependence framework, AI dependence is associated with the overuse of AI technologies, thereby giving rise to dependent and addictive behaviors. This might result in negative effects on students' interpersonal skills and mental health [19,21,24]. Some scholars also highlighted some negative outcomes of AI dependence, like risks to real-life relationships and emotional connections [24].

However, a few researchers believed that if there was widespread use of AI on campuses for higher education, it would not have a negative impact on students' minds and bodies [25–28]. Some scholars discovered that university life is connected to anxiety, tension, and stress, which are emotional states that AI may exacerbate or alleviate [29]. Some other studies have found that positive attitudes, positive subjective norms, and high perceived control are connected to more use of AI tools, which improves grades and mental health [30]. Some scholars stated that due to these more advanced NLP capabilities, some AI models may be able to help improve current mental health support frameworks for students' psychological well-being [31]. Zhai et al.'s findings provide evidence can support the idea that AI and mental health education together are effective means for fostering a mentally supportive academic atmosphere [32].

Against the backdrop of the rapid integration of AI into various educational domains, focusing on psychological health and well-being research within the higher education phase, particularly concerning the youth demographic, might hold significant contemporary value and practical necessity. This is primarily because higher education serves as a critical transitional period from campus life to the broader society. College students are at a crucial period of cognitive growth, personality formation, and social adjustment, a phase identified as Emerging Adulthood (a developmental concept covering adolescence to the mid-twenties, with a specific focus on the 18–25 age range [33]) by Jeffrey Jensen Arnett and broadly acknowledged by scholars. During this period, students' psychological resilience, emotional regulation, and interpersonal interaction patterns are still in a state of flux, making them more sensitive to the cognitive, emotional, and behavioral shifts introduced by new technologies. Secondly, college students represent a key population in AI-enabled education, as they need to develop essential competencies to effectively apply AI in their future professional practice [34,35]. This applies to all students, not only those in computer science, as they will likely need to use AI tools in their careers, regardless of their field or industry [36]. In fact, in higher education, AI-powered technologies have become essential tools for students, supporting their academic goals while also influencing how they spend their free time [37]. Thirdly, as digital natives and primary users of AI, university students offer a crucial perspective for exploring the long-term impacts of technology on youth mental health. Investigating their experiences can shed light on the mechanisms behind both the advantages and potential risks of AI use.

The psychological health of students is crucial not only for their academic development and life quality, but also to research efficiency and the long-term sustainable development of higher education [38]. However, there are few studies exploring the effects of AI on college students' mental health and well-being. Thus, this study intends to systematically review the influence of AI on college students' mental health and well-being in the higher education system. This study mainly takes Bronfenbrenner's Ecological Systems Theory (EST) as its theoretical foundation, while actively integrating insights from multiple disciplines to strengthen the study's conceptual framework. EST highlights that personal development is shaped by the interactions among multiple layers of the environment. The microsystem includes immediate contexts including the household, peer groups, and educational institutions, whereas the mesosystem captures the interrelationships among these settings; The exosystem involves indirect environments that affect the individual such as parents' workplaces or community resources; The macrosystem represents broader societal and cultural factors, including values, laws, policies, and economic conditions; And the chronosystem adds a temporal dimension, encompassing life transitions, historical events, and development over time [39–41]. In examining the effects of AI on college students' psychological wellness, it is essential to consider not only their internal psychological states but also how AI interacts with these multiple environmental layers. By providing a structured lens, the ecological systems framework enables researchers to systematically explore these complex and multi-level influences. Research questions are given below:

Q1: How does the integration and employment of AI technologies in higher education affect college students' mental health and well-being, including both potential benefits and risks?

Q2: What are the underlying psychological, social, and behavioral processes by which AI influences college students' mental health, considering factors such as reliance on AI, cognitive demands, emotional regulation, and interpersonal interactions?

Q3: How do contextual and environmental factors (including family, peer networks, campus culture, societal norms, and educational policies) shape the effects of AI application on college students' psychological health?

Q4: Which countries and regions have produced the largest number of academic publications on this topic in recent years, and what overall trends can be observed in their publication patterns?

2 Methods

This study employs a systematic review approach to analyze relevant literature. Trends, limitations, and potential future directions in existing research can be identified through a systematic literature review [42]. Clearly defined research questions, a comprehensive literature search and screening process, systematic approaches to data extraction and analysis, and compliance with transparent reporting standards are employed in this systematic review [43].

2.1 Design and Search Procedure

Scopus, EBSCOhost, and Social Sciences Citation Index (SSCI) (Web of Science) were searched in this study. Relevant studies published in major English-language journals were included: *Heliyon, International Journal of Instruction, JMIR Nursing, Frontiers in Psychology, Computer Science and Information Systems, JMIR mHealth and uHealth, Behavioral Sciences, Current Psychology, Healthcare, Frontiers in Education, International Journal of Engineering Pedagogy, Acta Psychologica, BMC Psychology, Psychiatric Quarterly, BMC Nursing, Language Testing in Asia, International Journal of Healthcare Information Systems and Informatics, Frontiers in Public Health, Education Sciences*, and *Education and Information Technologies*. The key search terms were ('artificial intelligence*' OR 'AI*') AND ('university student*' OR 'college student*' OR 'academy student*') AND ('mental health*') AND ('well-being*' OR 'wellbeing* OR 'happiness*' OR 'life satisfaction*') AND ('impact*' OR 'effect*' OR 'consequence*' OR 'influence*'). As of 29 January 2026, 1441, preliminary articles were initially identified. Following the removal of duplicate records, 1230 articles were obtained.

2.2 Selection/Extraction Process

We established inclusion criteria for the initial 204 retrieved publications to ensure the reliability and accuracy of the research to the research questions: (1) Peer-reviewed; (2) English-language journal article; (3) Employing empirical research methods (quantitative, qualitative, or a combination of both) [44]. After an initial examination of the abstracts and conclusions, 103 articles were suitable for inclusion in this research. The full text of these articles was obtained, and a review was carried out; a secondary screening was performed based on the following criteria (see Table 1 below). (1) The entire original article text can be downloaded; (2) the research focused on the impacts of AI on students' mental health and well-being; (3) the study centered on the postsecondary education context. Only articles investigating the direct impact of AI on the mental health of students in postsecondary education were included using these criteria. Substantive discussions typically centered on empirical investigations into the effects of AI on students' mental health and well-being, analyses of these effects based on empirical findings, or explorations of how AI shapes students' mental health (see Table 1 below).

Table 1: Screening criteria.

Eligibility Criteria:	Exclusion Criteria:
Written in English	Written in other languages
Empirical studies	Review papers, commentaries, or meta-analyses
Not duplicates	Duplicates
Full text obtainable	Full text unavailable
Journal articles	Non-journal publication
Concentrated on the higher education field	Not focused on the higher education field

After the secondary screening process was completed, 20 studies irrelevant to the research question were excluded from the final analysis. Additionally, 59 studies were excluded due to failing to meet our established eligibility criteria. Some were not rigorous empirical studies, some were not written in English, some did not provide full-text access (with certain tables or data unavailable), some were not published as academic papers, some did not focus specifically on higher education, and others had a Pubpeer record. Finally, 24 studies were included for the inclusion process of the study. PRISMA flow chart (see Fig. 1 below) shows 24 studies chosen for analysis. The author, year of publication, place of origin, theoretical model, research method, and the conclusion made from the research will be described.

Considering the limited number of eligible studies (24), we aim to adopt a broad inclusion approach and emphasize existing gaps to stimulate further empirical research. With respect to research methods and data types, we classified the empirical studies into 3 categories: quantitative, qualitative, and mixed methods approach. Of the 24 empirical research studies, 19 employed quantitative data analysis, 2 utilized qualitative approaches, and 3 adopted mixed methods. Quantitative data were primarily obtained from experimentally designed measures and questionnaire surveys conducted by researchers. Qualitative research data mainly included the data collected from the interviewees, such as educational staff members and students from higher education institutions of different countries. Most studies used experimentation, cross-sectional survey and other survey methods to study the effects of AI utilization on college students' mental health and overall wellness.

When it comes to evaluating the quality of research, the reviewed literature can be classified into 3 major groups according to distinct evaluation criteria: evaluation effect literature, descriptive literature, and explanatory literature. For both kinds of literature, whether descriptive and explanatory, the quality is determined by aspects like the reliability of the sources of information, the fit between the goals of the research and the methods employed, and the level of expertise of the researchers. But for qualitative studies about causal relationships, there's still no common quality evaluation system. This study covers two major aspects: (1) Validity of research, which includes the clarity and appropriateness of data acquisition and analytical methods used in the study, the data sources and analytical procedures verified by researchers, the reliability of respondent data, and the thoroughness in addressing unexpected or conflicting data found during the research process; (2) Relevance of research, considering whether the findings offer new insights or theories, the generalizability of the findings to comparable populations or settings, and whether the conclusions can be generalized to comparable situations.

This study presents a comprehensive review of the 24 included papers, synthesizing their key findings, research methodologies, and study designs. We studied the empirical outcomes found in the literature, with the goal of assessing how AI shapes students' mental health and life satisfaction in the context of postsecondary education. Data analysis was carried out in two phases employing a structured coding framework. In the first stage, each article was scrutinized to find unique codes and create a complete codebook. Subsequently, different analytical methods, including regional distribution analysis and main topics analysis, were adopted to solve the research problems (see Fig. 1 below).

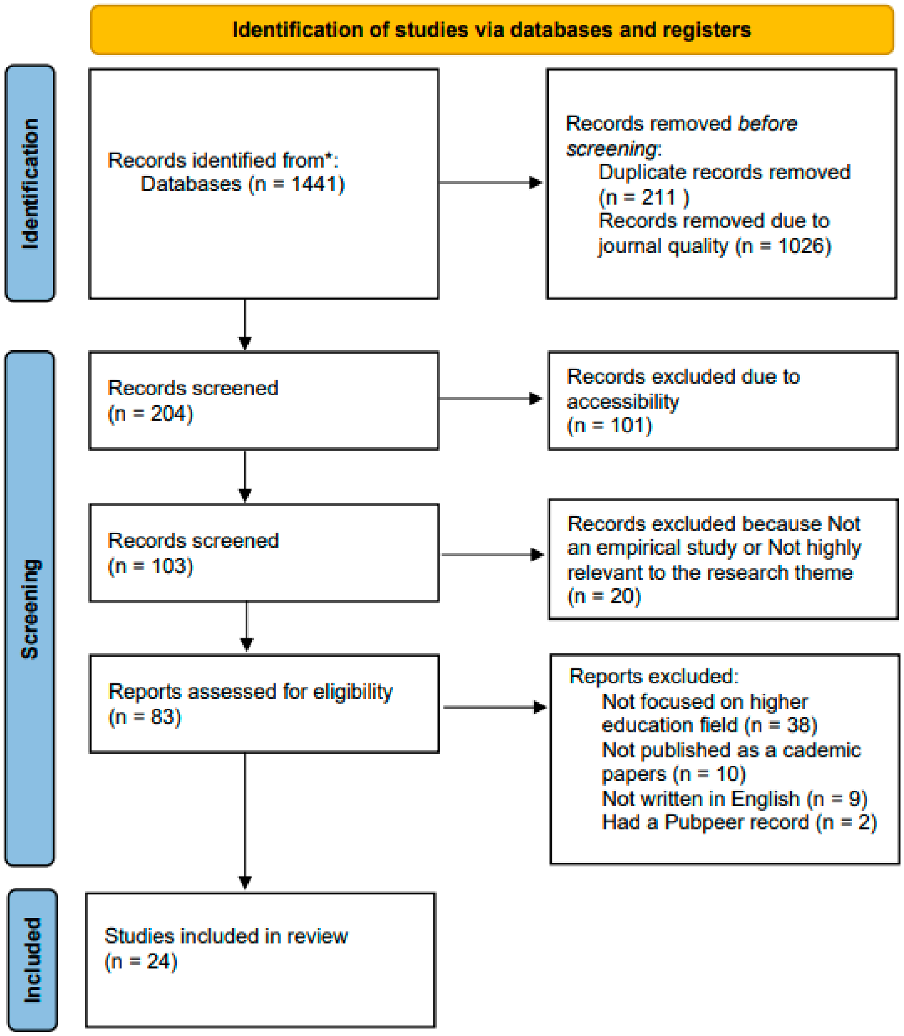

Figure 1: Prisma flowchart for study selection.

2.3 Quality Assessment

This study applied several tools to evaluate the quality of selected publications. For assessing selected quantitative studies, the Joanna Briggs Institute (JBI) tool was utilized in this study [45]. The Critical Appraisal Skills Programme (CASP) instrument was employed to evaluate the methodological quality of the included qualitative studies [46]. Regarding mixed methods studies, quality evaluation was performed using the Mixed Methods Appraisal Tool (MMAT) [47]. Eight separate criteria were utilized in the JBI tool for the appraisal of quantitative studies, encompassing sample inclusion criteria, measurement of exposure variables, study subjects and settings, identification of confounding factors, control of measurement conditions, strategies to address these confounders, outcome measurement, and data analysis techniques [48]. Ten specific criteria for qualitative studies were evaluated using the CASP tool, covering research objectives, study design, methodology, recruitment approach, methods of data gathering, data analysis procedures, researcher-participant relationship, findings, ethical considerations, and the broader implications of the study. For mixed methods studies, five key components were assessed using the MMAT, encompassing the methodological elements, the justification for the adopted methods, the interpretation of results, the research questions and aims, as well as the potential sources of bias. Assessment scores were ultimately standardized on a ten-point scale. Every assessment was carried out independently by two researchers on two distinct occasions.

On this basis, this research used the kappa statistic to examine the level of agreement between raters. When data were collected from multiple evaluators, interrater reliability (also known as inter-rater agreement) was routinely assessed using Cohen's kappa and related statistics to quantify consistency in categorical variables [49]. Cohen's Kappa, defined by the formula:

$$\kappa = Po - Pe/1 - Pe \tag{1}$$

This formula quantifies interrater reliability, where Po represents the relative observed agreement among raters and Pe denotes the hypothetical probability of agreement occurring by chance [50,51]. According to Cohen, Kappa values can be classified as follows: values of $\kappa \leq 0$ reflects no agreement, 0.01–0.20 represents slight agreement, 0.21–0.40 denotes fair agreement, 0.41–0.60 signifies moderate agreement, 0.61–0.80 suggests substantial agreement, and 0.81–1.00 demonstrates near-perfect agreement [52]. And this study's interrater reliability, as computed via Cohen's Kappa coefficient, exceeded 0.82, reflecting considerable agreement and thus demonstrating satisfactory reliability. The quality assessments revealed that 23 of 24 studies (95.833%) were judged to be at low risk of bias, which implied that the included studies were generally of high quality. The specific details can be seen in Table 2.

Table 2: Quality assessment of the selected studies.

Authors	Methodology	Appraisal Instruments	Scoring Result	Level of Risk	Cohen's Kappa
Shahzad et al., 2024 [25]	Quan	JBI	10	Low	1
Abdul Rahman et al., 2023 [53]	Quan	JBI	10	Low	1
Alshammari, 2025 [54]	Mixed	MMAT	10	Low	1
Hao et al., 2025 [26]	Quan	JBI	10	Low	1
Alshowkan & Shdaifat, 2025 [55]	Quan	JBI	10	Low	1
Fan & Song, 2025 [56]	Quan	JBI	10	Low	1
Wang et al., 2025 [57]	Quan	JBI	10	Low	1
Wang & Wang, 2024 [58]	Quan	JBI	9.375 (Low)	Medium	0.875
Ma et al., 2024 [59]	Quan	JBI	10	Low	1
Cengiz & Peker, 2025 [60]	Quali	CASP	10	Low	1
Albikawi et al., 2025 [61]	Quan	JBI	10	Low	1
Morales-García et al., 2024 [62]	Quan	JBI	10	Low	1
Liang et al., 2022 [63]	Quan	JBI	10	Low	1
Ajlouni et al., 2024 [64]	Quan	JBI	10	Low	1
Li et al., 2025 [28]	Quan	JBI	10	Low	1
Lin & Chen, 2024 [65]	Mixed	MMAT	10	Low	1
Erdemir & Atik, 2025 [66]	Quali	CASP	10	Low	1
Ayed et al., 2025 [67]	Quan	JBI	10	Low	1
Khasawneh et al., 2024 [68]	Quan	JBI	10	Low	1
Wang & Xu, 2026 [69]	Quan	JBI	10	Low	1
Jiang, 2025 [70]	Quan	JBI	10	Low	1
Robayo-Pinzon et al., 2025 [71]	Quan	JBI	10	Low	1

Table 2: *Cont.*

Authors	Methodology	Appraisal Instruments	Scoring Result	Level of Risk	Cohen's Kappa
Delello et al., 2025 [27]	Mixed	MMAT	10	Low	1
Zhai et al., 2025 [32]	Quan	JBI	10	Low	1

Note: JBI: Joanna Briggs Institute Critical Apprasial tools; MMAT: Mixed Methods Appraisal Tool; CASP: Critical Appraisal Skills Programme Tool; Quan: Quantitative; Quali: Qualitative; Mixed: Mixed Study.

3 Results

3.1 Regional Distribution and Publishing Trend Analysis

There are different regional distribution characteristics. The countries and areas involved in the dataset have a relatively small range; some countries appear several times. The region's most often involved are China, Saudi Arabia, Turkey, Jordan, Brunei, Peru, Palestine, Colombia, and the USA. Of the included papers, 12 were published in China, 3 in Saudi Arabia, 2 in Turkey, 2 in Jordan, and one each in the USA, Brunei, Peru, Palestine, and Colombia. Among the 6 of the above-mentioned countries, China, Saudi Arabia, Brunei, Palestine, Jordan, and Turkey are from Asia, Peru and Colombia are from Latin America, the USA is from North America, and there are no related articles from Africa, Europe, or Oceania. The data above suggests that researchers from Asia, particularly those from China, appear to engage more frequently with this topic. In comparison, researchers from other continents show relatively lower levels of engagement, although interest among researchers from Saudi Arabia seems to have gradually increased in recent years. But the traditional powerhouses like the United Kingdom, Germany, and Japan still have not placed much weight on this problem (see Fig. 2 below).

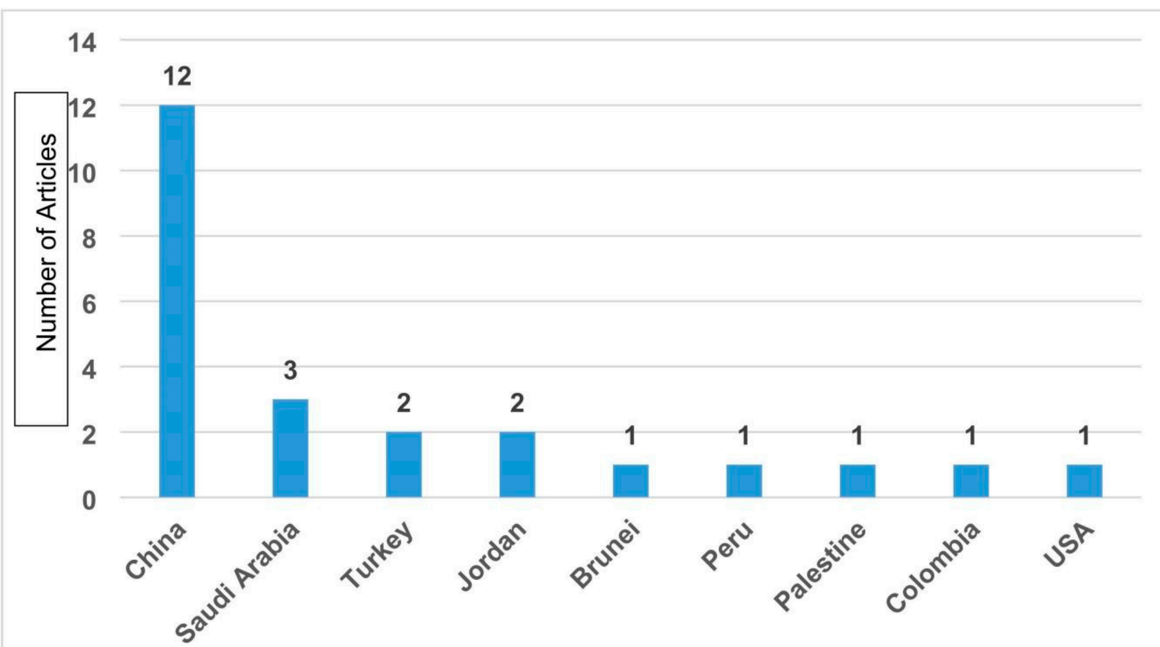

Figure 2: Overview of the regional distribution analysis of the selected publications.

A detailed statistical analysis of the institutions of the first authors of the selected works shows that most of the first authors work at higher education institutions, with only 1 first author working at a research institution. A single first author is affiliated with institutions in both the United States and Brunei (see Fig. 3 below), which is why there are 24 articles but 25 first-author affiliations (see Table 3 below). Schools are more focused on this topic than research institutions and industrial sectors.

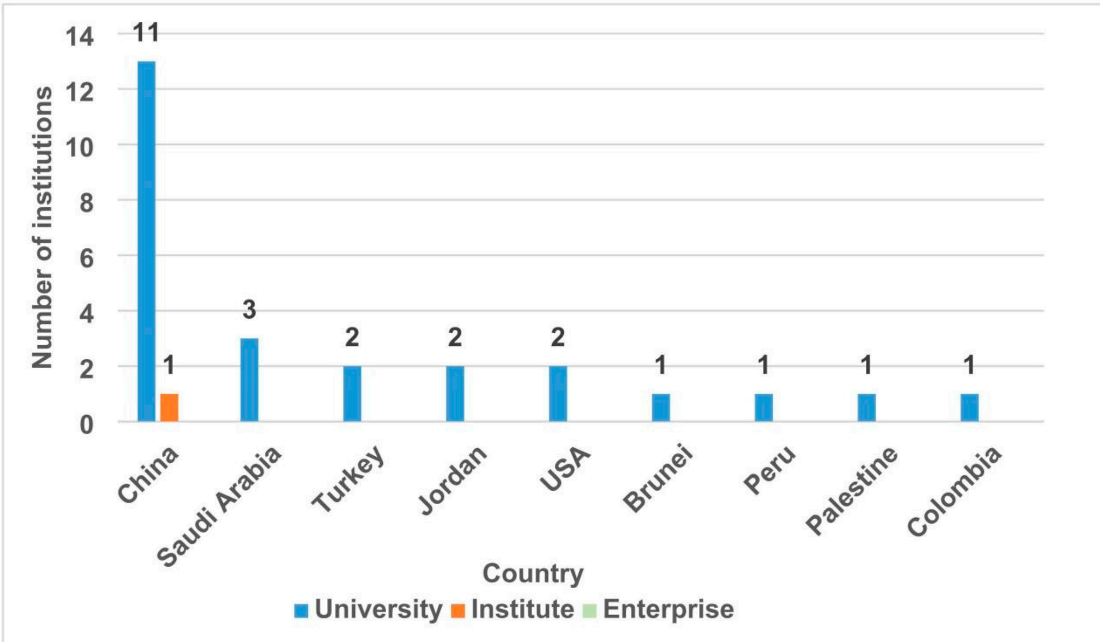

Figure 3: Overview of the regional distribution analysis of the institutions for the first authors.

Table 3: List of institutions for the first author.

Country	Number of Institutions	Institutions for The First Authors List
China	12	Beijing University of Science and Technology, Guangzhou College of Commerce, Chongqing Technology and Business University, City University of Hong Kong, Zhoukou Vocational and Technical College, Zhejiang Sci-Tech University, Changsha Normal University, Wenzhou University, Tianjin Foreign Studies University, Henan Technical Institute, Yangzhou University, Shanghai International Studies University
Saudi Arabia	3	College of Education and Human Development, King Khalid University, Imam Abdulrahman Bin Faisal University
USA	2	The University of Texas at Tyler, University of Michigan, Ann Arbor
Turkey	2	Ağrı İbrahim Çeçen University, İnönü University
Jordan	2	Yarmouk University, The University of Jordan
Peru	1	Universidad Peruana Unión
Palestine	1	Arab American University
Colombia	1	Universidad del Rosario
Brunei	1	Universiti Brunei Darussalam

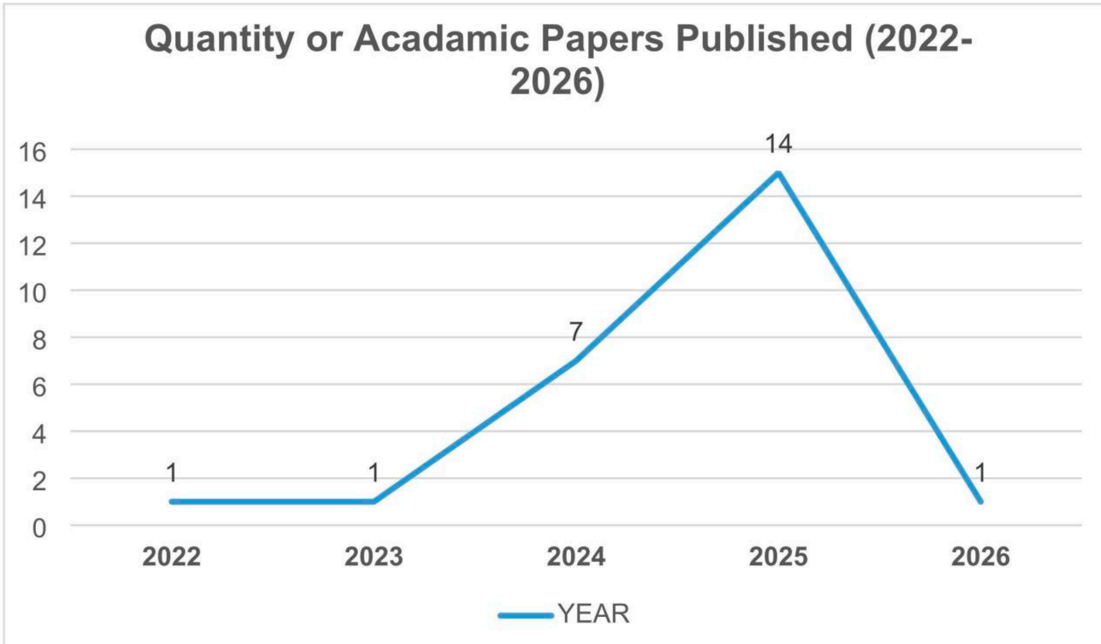

Figure 4: Temporal trends of the included studies.

The earliest articles on this topic were published in 2022. And between 2022 and 2023, 2 studies were published, with 1 study appearing each year. There has been a sudden growth in the number of publications in this area in 2024. A total of 7 relevant studies appeared in 2024, with the figure increasing to 14 in 2025. As of the end of January 2026, only 1 academic paper related to this topic has been published. This upsurge showed that this subject has drawn more attention and interest from academics in recent years (see Fig. 4 above and Table 4 below).

Table 4: Overview of the selected 24 articles.

Authors	Sample Size	The Specific AI Tools Assessed	Research Methods	Findings Summary
Shahzad et al., 2024	401	Mainly focusing on AI as a whole, with a particular emphasis on generative AI like ChatGPT	Quantitative study	Chinese students viewed AI and social media as positive influencers of academic performance and mental health; Smart learning can be a mediator that can provide an evidence-based policy framework [25].
Abdul Rahman et al., 2023	15,366	Machine Learning Classifiers	Quantitative study	This study is using machine learning algorithms to make a model and prediction of negative mental well-being by finding out important things such as physical activities, BMI, GPA, sedentary behavior, and age; Random Forest and adaptive boosting have the most correct results when it comes to finding out who will get mental health issues among Southeast Asian university students [53].
Alshammari, 2025	365	ChatGPT	Mixed study	This study focuses on how well ChatGPT works as an AI supporter to make university students feel better emotionally, and it seems good at dealing with stress and worry, but there's still some room for making it even more personalized and improved [54].
Hao et al., 2025	484	AI-assisted psychological intervention mechanisms	Quantitative study	The present study underscores the novel application of AI models within psychological intervention practices. It illustrates how intelligent perception, real-time feedback, and dynamic adjustments can improve the accuracy and effectiveness of mental health support services in postsecondary education [26].
Alshowkan & Shdaifat, 2025	497	Mainly focusing on AI as a whole	Quantitative study	This study demonstrates that AI literacy influences psychological empowerment, trait anxiety, and overall well-being, indicating its significance for bettering well-being results among different sexes [55].
Fan & Song, 2025	80	The interactive technology in AI	Quantitative study	AI-driven voice interaction and self-efficacy analysis improve mental health education by film courses [56].
Wang et al., 2025	100	CBT-based AI chatbot	Quantitative study	Culture-adapted CBT-based AI chatbot effectively mitigated depression and feelings of loneliness among Chinese university students, particularly those with high financial stress, showing its potential as an accessible mental health resource [57].
Wang & Wang, 2024	2423	Mainly focusing on AI as a whole	Quantitative study	This study contributes to the growing literature on AI's role in academic settings and provides actionable insights for enhancing mental health support within academic environments [58].

Table 4: *Cont.*

Authors	Sample Size	The Specific AI Tools Assessed	Research Methods	Findings Summary
Ma et al., 2024	356	Mainly focusing on AI as a whole	Quantitative study	AI boosts students' innovative behavior & teaching effectiveness, and well-being mediates these effects [59].
Cengiz & Peker, 2025	494	Generative AI	Qualitative study	Generative AI acceptance reduces AI anxiety; the UTAUT framework, AI attitudes, and literacy mediate acceptance; more frequent use and societal benefits recognition are needed [60].
Albikawi et al., 2025	176	AI-driven mental health supporting tools	Quantitative study	AI-based mental health promotion instruments show promise as supplementary support to standard counseling services among nursing students who are upset, but worry about personal info safety, unfairness, and feeling human stress out point at having things done morally and mixing up treatment ways [61].
Morales-García et al., 2024	528	Construction and validation of a scale for assessing dependence on AI	Quantitative study	The DAI scale is a good way to see how much college kids rely on AI; it doesn't change based on whether they're boys or girls. This shows we should know about people and AI together in our digital world for everyone to get along [62].
Liang et al., 2022	5058	IoT-based interventions for mental health education and convolutional neural network (CNN)	Quantitative study	Develops AI/big data mental health platform for sports majors (CNN early warning) [63].
Ajlouni et al., 2024	340	Chatbot-based AI	Quantitative study	The study has discovered a strong positive relationship between the extent of AI-powered chatbot use and scholastic well-being in undergraduates, which means adding AI tools to studying could lead to better grades [64].
Li et al., 2025	468	Mainly focusing on AI as a whole	Quantitative study	Responsible teachers, AI, and peer collaboration jointly enhance student well-being; proposes support ecosystem (human/technical/social); recommend teacher training and peer learning [28].
Lin & Chen, 2024	150	Mainly focusing on AI as a whole	Mixed study	AI integration into education will promote creativity and engagement, but it also brings problems such as creativity limits, emotional disengagement, and performance anxiety, so we need to pay attention to its implementation and continuous assessment [65].
Erdemir & Atik, 2025	1184	The AI-Digital Life Balance Scale (AI-DLBS)	Qualitative study	AI-assisted (ChatGPT) scale assesses students' digital life balance, 6-factor structure: psychological/social/physical/academic; valid and reliable; needs testing across diverse populations [66].

Table 4: *Cont.*

Authors	Sample Size	The Specific AI Tools Assessed	Research Methods	Findings Summary
Ayed et al., 2025	264	AI integration in healthcare education	Quantitative study	Negative attitude and limited AI exposure, particularly for younger females and non-users, cause anxiety in Palestinian nursing education, which requires AI literacy, practical experience, and gender-awareness training [67].
Khasawneh et al., 2024	391	Mainly focusing on AI as a whole	Quantitative study	This research focuses on how learner autonomy is related to academic buoyancy, psychological wellness, and scholastic performance in AI-supported computer-assisted language learning. It points out that autonomy and buoyancy are important for the psychological well-being of EFL students [68].
Wang & Xu, 2026	624	AI tools	Quantitative study	This study looks at how using AI tools in school affects being stressed out about schoolwork. It finds that feeling lonely is why this happens, and feeling good about your own studying skills makes things better when you use AI and feel lonely [69].
Jiang, 2025	98	Deep Learning	Quantitative study	Deep learning + remote platforms improve vocational college psychology teaching [70].
Robayo-Pinzon et al., 2025	420	Generative AI	Quantitative study	This study reveals that young individuals generally exhibit low levels of dependency on generative AI tools. Their proficiency in using such tools is influenced by both the duration of usage and waiting scenarios, highlighting the need for further research into the perceived importance of AI and the key factors that motivate people to adopt and use these technologies [71].
Delello et al., 2025	353	Mainly focusing on AI as a whole	Mixed study	AI affects how teaching works and students' feelings; says to trust AI, do right by it, and help teachers with AI skills; about being honest and sharing on computers; needs rules about using AI responsibly [27].
Zhai et al., 2025	600	Deep Learning	Quantitative study	AI-powered solutions are improving mental health services; stress mental health education, digital learning synergy, and supportive policy [32].

3.2 AI's Negative Impacts on College Students' Mental Health and Well-Being

Some studies pointed out that the implications of AI on university students should be linked to the four parts: personal psychology, social well-being, physical health, and academic performance [67]. Therefore, this study will examine the negative effects of AI on the psychological health and well-being of students in the following four dimensions and analyze the deep factors of these negative psychological effects caused by AI on social interaction, physical health, and academic well-being. According to evidence derived from this review, deep integration of AI in tertiary education may cause some negative emotions for students, such as anxiety, alienation, and stress.

AI-induced Anxiety as a Major Psychological Issue Among College Students. Anxiety among students caused by AI might come from the change in their learning methods due to the revolution of technology led by AI. Traditional classroom learning methods are changing, and students are forced to accept and use the new learning methods and tools brought by AI. This shift imposes a higher cognitive burden on the students and creates obstacles in their understanding of the technology, which adds to the feeling of anxiety. Some scholars said that during the pandemic, students became significantly more anxious because they had to change how they learned suddenly, lacked in-person social interaction, and didn't know what would happen to them in the future [72]. The changes in learning methods that caused the increase in student anxiety were a result of the increase in the integration of AI in university-level education during the pandemic, because of space limitations. Social interaction can help to ease anxiety, with high levels of social support being associated with low levels of anxiety [73]. But a widespread use of AI can further isolate people and create more atomized students [27]. Unlike traditional classroom instruction, AI-enabled education (AIED) drastically reduces the opportunities for, and frequency of, student-teacher interactions as well as student-student (peer) interactions. On the contrary, it is human-machine interaction that increases, thus affecting students' ability to control their own anxiety and even giving birth to new types of anxiety.

AI-induced Alienation or Social Isolation as a Major Psychological Issue Among College Students. From psychological and social aspects, alienation or social isolation might be another psychological issue caused by AI. The impersonal characteristics of AI-based learning may erode the relationship between teachers and students and reduce the chances of social interaction and empathy in an educational setting [74]. The increasing dependence on AI technology might make it so that teachers and students end up not knowing each other very well, and this might be detrimental to students' sense of school belonging [27]. When AI is adopted in the educational circle, the relationship between teachers and students, and students with students will be changed, as well as students will become increasingly detached from their teachers, classmates, and even society. Studies implied that as AI integrated more into educational settings, there was a potential for unintentional social isolation or alienation, and that this could be a recognized risk factor for various mental health issues [75].

AI induced Loneliness as a Major Psychological Issue Among College Students. In addition, focusing on the social aspects, existing literature mentioned that the overuse of artificial intelligence can increase levels of loneliness among students [37,74,76]. Many researchers have pointed out that an increase in the adoption of AI-based tools will be one of the most obvious drawbacks to the development of tertiary education through the combination of AI and postsecondary education [77,78]. Crawford et al. carried out empirical research and proved that social support could moderate the connection between loneliness and AI usage, which means that when students feel that AI is the most important "person" they rely on, loneliness would rise [79]. In addition, according to Nakshine et al. [18], the widespread use of AI results in prolonged screen time and causes digital fatigue, loneliness, anxiety, and other mental health problems among students. Excessive reliance on AI might lessen the chances that students have for actual face-to-face social activities, which could then damage the abilities they have for talking to people and sensing emotions, exacerbating feelings of loneliness [80].

AI-induced Stress as a Major Psychological Issue Among College Students. Stress is a major potential negative psychological impact in academic terms. The primary stress induced by AI is academic stress, which is largely caused by new study demands placed on college students by AIED widely applied in education. AI and higher education are deeply integrated, which makes college students learn to adapt to complex technologies, creating new pressure and increasing the burden of learning, even causing technostress and burnout [81]. A more recent study also found that 77% of participants who used AI tools said their productivity went down and they experienced increased workloads [82].

3.3 AI's Positive Impacts on College Students' Mental Health and Well-Being

Many studies have also indicated that AI utilization may exert favorable psychological impacts on university students, which can be prominently reflected in the selected 24 publications as well. The constructive impact of AI on the mental health of college students might be largely realized through the deep integration between AIED and university-level education and the wide utilization of AI tools in the higher education system.

AI as a Facilitator for Boosting Psychological Wellness and Mental Health within Postsecondary Education. AIED can enhance students' learning experience and well-being by addressing individuals' learning needs [28]. AI tools can streamline repetitive tasks, offering personalized resources and facilitating self-paced learning, thereby helping to alleviate the burden of excessive workload on students [83]. Some researchers suggested that personalized AI-driven learning processes, aligned with the personalized needs of learners, may help alleviate academic stress [84]. The functions of AI tools align with the fulfillment of learners' demands for independence and competence, as outlined in self-determination theory, and thus can be instrumental in boosting students' emotional well-being [85].

Furthermore, AI brings about beneficial outcomes for students through the deep integration into education and can promote ongoing student psychological health via many AI-powered software and systems for academic and non-academic purposes in higher education. Research investigating the impact of conversational agents (CAs), widely used by both scholars and the public, indicates that these tools are effective in improving users' emotional well-being. They can alleviate feelings of sadness, fear, or distress, and may also contribute to greater happiness and enjoyment in daily life [86,87]. AI-driven systems, which are constructed via a framework of reinforcement learning, have proved to be conducive to improving such mental health conditions as anxiety in accordance with the findings by Cengiz and Peker [60]. Moreover, AI has been successful in identifying mental health risks, offering interventions, and boosting cognitive engagement and emotional regulation [88]. Guo and Liu emphasize that institutions ought to harness AI and big data technologies to precisely pinpoint high-risk subgroups and deliver tailored and practical interventions as well [38].

An Examination of AI's Impacts on Students' Mental Health through Bronfenbrenner's Ecological Systems Theory. Drawing on EST [89], Li et al. viewed teacher-provided support as a proximal predictor (microsystem), technological integration as an instructional resource (ecosystem), and peer collaboration as a component of the direct social environment impacting students (microsystem/mesosystem) and found that teacher guidance, technological assistance and student engagement could be interdependent, with AI serving as a key mediating factor through which the responsibility borne by teachers affects students' scholastic and emotional welfare [28]. In other words, AI can indirectly promote students' mental health by actively fostering the development of a supportive educational ecosystem (see Fig. 5 below).

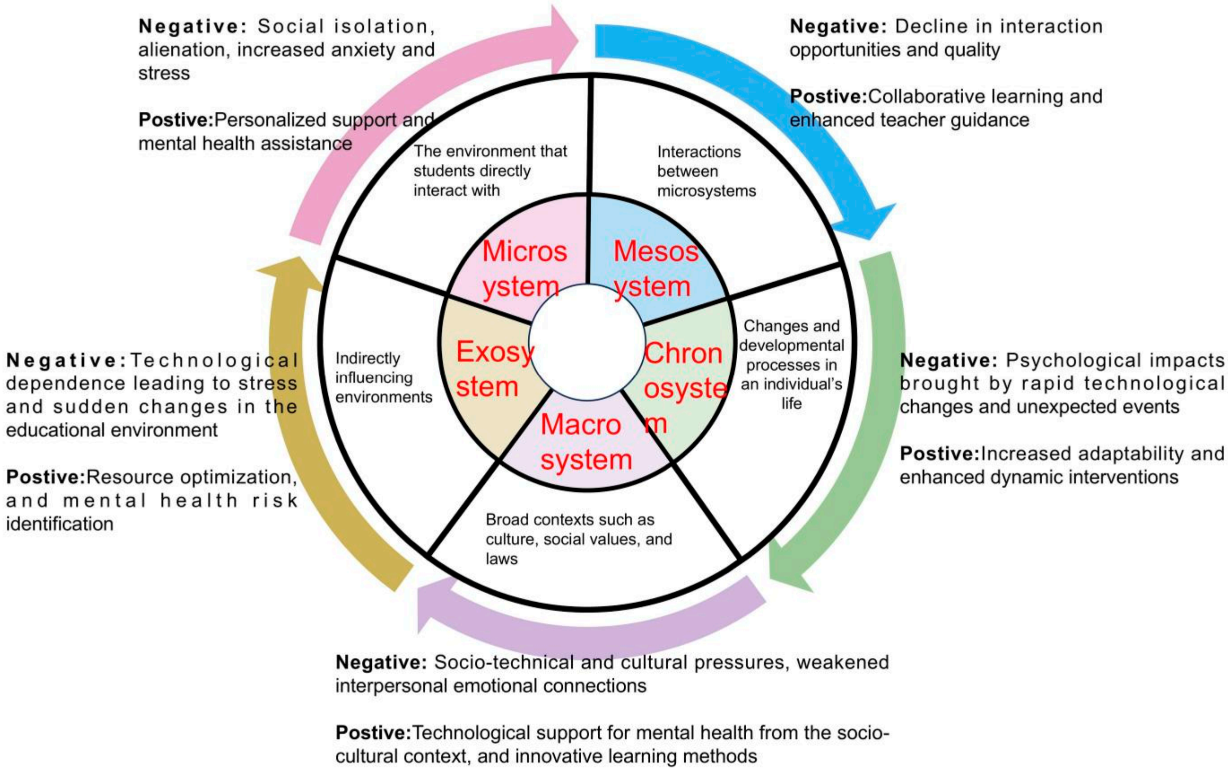

Figure 5: Theoretical framework diagram of the impact of AI on college students' mental health and well-being.

This theoretical framework, grounded in EST, provides a relatively integrated and detailed depiction of how AI affects students' well-being. AI plays distinct roles in influencing college students' mental health across different systemic levels, producing both positive and negative effects at each level. For example, from the exosystemic perspective, the integration of AI functions as an external technical resource with indirect effects in enhancing teaching practices and customizing instructional environments, thereby contributing to the development of an AI-empowered educational ecosystem [90]. The various ecological systems are interconnected, forming a cyclical chain of influence. The macrosystem, encompassing culture, laws, economic conditions, and policy frameworks, shapes how ecosystems operate. Although students do not directly engage with ecosystem elements such as institutional resources or social structures, these factors indirectly affect their psychological development and well-being through microsystems. The mesosystem, in turn, consists of the relationships and interactions between different microsystems. Microsystems provide direct experiences, while the mesosystem coordinates and links these experiences, thereby indirectly influencing psychological development and social behavior. Furthermore, the patterns of interaction within the mesosystem evolve over time. The chronosystem represents the temporal dimension, illustrating how changes in the macrosystem (such as social development, policy reforms, or cultural shifts) progressively influence microsystems and ultimately the individual.

4 Discussion

Artificial intelligence is related to higher education; the continuing development of AI-driven teaching products will be able to promote mental health and happiness among college students. AI-driven technologies like intelligent conversational agents or VR simulations have the power to transform the mental health intervention environment for university students [91]. Bronfenbrenner's Ecological Systems

Theory provides an effective theoretical framework for exploring the impact of AI technology on college students' mental health. This theory emphasizes the interactions of individuals within multi-level social environments [92]. Through this framework, researchers can also gain insights from various perspectives on how external socio-cultural factors shape students' psychological responses to AI and how different ecological levels collectively influence their mental well-being [93]. Therefore, future research on this topic could benefit from examining how ecological factors at different levels may influence the implications of AI tool usage. Building on EST, which outlines five systems, we found that it could be important to explain AI's impact on college students' mental health by integrating multiple theoretical perspectives. At the macro and ecosystem levels, where cultural and societal contexts play a pivotal role, Bandura's Social Cognitive Theory (SCT) and Hall's Contesting Model are utilized to provide explanatory insight. At the microsystem, mesosystem, and chronosystem levels, attention shifts to individual psychological responses and developmental processes. To capture these aspects, various psychological frameworks (including Cognitive Load Theory (CLT), Self-Determination Theory (SDT), Stress-Coping Theory, and Resilience Theory) are applied to analyze students' mental health outcomes in depth.

Considering differences in external environments, future research could benefit from examining regional variations in socio-cultural contexts, as this may help to better understand and reduce the potential negative impacts of AI use on students' mental health and well-being. The United Nations Educational, Scientific and Cultural Organization (UNESCO) defines culture as "the set of distinctive spiritual, material, intellectual and emotional features of society or a social group, and that it encompasses, in addition to art and literature, lifestyles, ways of living together, value systems, traditions and beliefs" [94]. Context can be understood as an environmental system comprising participants, events, environments, and a focal entity [95]. Cultural context is closely linked to place identity, which shapes human-environment interactions [96], and its influence is contingent on specific situational settings [95]. Bandura's SCT highlights reciprocal dynamics across personal, behavioral, and contextual factors, emphasizing that cognition, behavior, and environment co-shape individual learning and development [97]. Socio-cultural context, as a macro-level factor, significantly affects how AI influences college students' academic performance and mental health across cultures. Students from different cultural backgrounds may engage with AI differently, resulting in varied psychological responses and learning outcomes. According to Hall's contacting model, cultures are classified as high- or low-context, reflecting the implicitness of communication [98]. High-context cultures, common in Asia, Africa, the Arab world, Central Europe, and Latin America, rely on non-verbal cues and shared understanding, whereas low-context cultures, typical in Western Europe, the United States, and Australia, prioritize explicit verbal communication and individual style [99,100]. Many AI applications in higher education fail to consider these cultural differences, potentially producing inconsistent academic results and psychological effects. Therefore, AI tools should be culturally adapted to ensure their effectiveness and appropriateness in diverse educational settings globally.

Furthermore, we argue that future research should continue to investigate the underlying mechanisms through which AI impacts college students' mental health and well-being in higher education. Such investigations would benefit from the integration of insights from psychology, education, sociology, and other relevant disciplines. In this study, we attempt to elucidate these mechanisms by drawing on several established psychological frameworks.

From the perspective of CLT, the complexity of information and task design within AI systems can significantly heighten students' cognitive processing demands. CLT categorizes cognitive load into three types: intrinsic load (inherent complexity), extraneous load (unnecessary effort), and germane load (learning effort), each of which draws upon the finite resources of working memory [101,102]. And according to

CLT, instructional design should not only recognize but also actively manage the three distinct types of cognitive load to optimize learning outcomes [103]. In higher education, AI technologies are increasingly employed in intelligent learning platforms, automated assignment grading, personalized recommendations, and data analytics. If these systems are poorly designed, students may encounter confusion in navigating interfaces or comprehending content, thereby exacerbating psychological stress. Conversely, well-designed AI applications can streamline information presentation, reduce extraneous cognitive load, and offer timely feedback along with tailored learning paths, ultimately alleviating cognitive strain and enhancing both learning efficiency and psychological comfort.

Secondly, AI has a significant impact on fulfilling college students' basic psychological needs. SDT posits that social environments influence human functioning by either supporting or undermining the satisfaction of three fundamental psychological necessities: autonomy, mastery, and affiliation [104,105]. SDT further suggests that social environments that support basic psychological needs enhance individuals' intrinsic motivation and overall well-being [106]. And the introduction of AI transforms the external social environment, potentially reshaping the ways in which students' basic psychological needs are supported. In higher educational contexts, AI that excessively intervenes in the learning process may undermine autonomy, reducing both motivation and psychological satisfaction. Conversely, AI can enhance students' sense of competence through personalized learning recommendations, intelligent tutoring, and timely feedback, allowing learners to clearly perceive improvements in their abilities and thereby boosting self-esteem and a sense of achievement. Furthermore, AI systems with social features, such as virtual learning companions or online collaboration tools, can help satisfy the need for relatedness, alleviating feelings of isolation and supporting overall psychological well-being.

From the perspective of Stress-Coping Theory, AI may significantly influence how college students perceive and respond to academic stress, thereby affecting their mental health and overall well-being. This theory suggests that psychological outcomes emerge from the interplay between perceived stressors and the coping resources available. According to Lazarus' transactional model, stress is understood as a process through which individuals evaluate environmental demands in relation to their perceived coping resources [107]. This process involves primary appraisal, where one assesses whether an event poses a threat to personal well-being, and secondary appraisal, which examines the available means of control and support [108]. A situation is deemed stressful only when it is considered personally relevant and exceeds the individual's current capacity to cope [109]. Within higher education, AI that overly controls the learning process can become an added stressor, diminishing students' sense of control and heightening feelings of anxiety or frustration. On the other hand, AI can serve as a supportive resource by delivering personalized learning guidance, intelligent tutoring, and timely feedback, enabling students to handle academic demands more effectively, lower perceived stress, and enhance their sense of competence. By shaping both stressors and coping mechanisms in educational contexts, AI can have either beneficial or detrimental effects on students' mental health and well-being, depending on how it is designed and applied.

Lastly, students' ability to cope with challenges arising from AI-mediated learning and daily life represents a key factor influencing their mental health. Resilience describes the capacity of individuals to sustain psychological well-being even when confronted with significant psychological or physical challenges [110]. Research on resilience highlights the importance of both external supports and individual internal capacities [102]. Within AI-driven learning environments, issues such as technical malfunctions, the complexity of learning tasks, and concerns about assessment transparency may pose significant challenges for students. Those with higher levels of psychological resilience are better equipped to navigate these changes, regulating their emotions and coping strategies effectively, thereby reducing feelings of anxiety and depression. Educators and policymakers can further support students by leveraging AI to provide timely feedback, customizable learning pathways, and mental health prompts, ultimately fostering adaptive capacity and enhancing resilience.

5 Conclusion

Our study offers a systematic synthesis of relevant literature on how AI affects the mental health and well-being of college students. It answers the three major research questions in depth. Firstly, in terms of the main characteristics of AI influencing students' mental health in higher education, we find that most studies focus on the individual psychological effects of AI and most emphasize micro-level factors. Just a handful of studies consider the broader macro-level ramifications of AI within higher education, as well as the potential influences of its widespread adoption on public policy modifications. The existing studies attract considerable attention among scholars across different countries, with China receiving the most attention. The research objects are students' learning results, potential mental health risks, cognitive engagement, emotional management, integration of ethical AI, AI framework, application of AI tools, educational reform measures, and their practical results. A variety of research methods and designs were employed. In the conceptual framework and theoretical model, we mainly studied three parts of this project: technology ethics, cognition, and behavior. And we tried to explore the impact of artificial intelligence on college students' mental health, considering both its potential benefits and detrimental effects on their overall well-being. Secondly, the main issues concerning the impact of AI on the mental health and well-being of college students are concentrated on the aspect that AI can promote the mental health of college students by applying beneficial applications, and the ethical issues related to the application of technology. The systematic review of the existing literature shows that the application of AI in higher education can promote college students' innovative behavior and improve the effectiveness of teaching. AI can contribute to the overall improvement of academic performance and mental health, such as reducing anxiety and depression. And further, AI use has the potential to even increase college students' emotional intelligence. But some scholars have also mentioned that artificial intelligence might cause more negative emotions, like being worried, feeling lonely, or having too much stuff to think about (Links to supplementary materials are available in the section titled "Supplementary Materials" at the end of this paper).

6 Limitations and Future Directions

The present study is not without limitations. At present, the studies on the influence of AI applications on learners' mental health and general welfare are mainly carried out in Asian countries and the United States. Therefore, this systematic review does not give a full representation of the situation in other regions and countries around the world.

Based on Hall's Contexting Theory, it can be observed that the research included in this study primarily focuses on high-context culture countries, such as China, Saudi Arabia, Turkey, Jordan, Brunei and Palestine, while studies from low-context culture countries are relatively scarce. Notably, the study does not include other significant low-context culture countries, such as the United Kingdom, Canada, or the Nordic countries. This limitation in sample selection may result in geographic bias, thereby affecting the breadth and generalizability of the findings. Moreover, existing research overlooks the potential impact of this geographic bias. The cultural differences between low-context and high-context societies may lead to distinct patterns in how AI influences students' mental health and academic stress. Low-context cultural countries tend to favor explicit communication and information transmission, which may make students more receptive to AI, which may make students more receptive to AI and better equipped to recognize and cope with the academic pressure generated by AI. In contrast, high-context culture countries rely more on background information and implicit communication, which could influence students' perception and acceptance of AI. Consequently, students from high-context cultures may experience different mental health responses to AI-induced academic pressure, with varying coping mechanisms. Moreover, cultural differences in the perception of academic stress and tolerance levels may also play a significant role. In some high-context culture countries, students might have a higher tolerance for academic pressure stemming from external sources such as AI systems, whereas students in low-context culture countries might be more sensitive to such stress, potentially leading to more pronounced mental health challenges. Therefore, future research needs to carefully consider these cultural variations and investigate how AI impacts students' mental health across different cultural contexts. This will help ensure that findings are more culturally nuanced and applicable across diverse educational environments.

Moreover, to acquire a more comprehensive insight into how AI affects students' mental health, future research should foster interdisciplinary collaboration across disciplines such as psychology, education, ethics, artificial intelligence, and sociology. Researchers from diverse academic backgrounds can jointly develop multidimensional assessment tools that focus on both the short-term and long-term effects of AI on college students' mental health. These tools should integrate psychological assessments, behavioral data analysis, and AI technologies to evaluate the long-term impact of AI on students' mental well-being, academic performance, and social adaptability. Additionally, it is recommended that enterprises such as OpenAI consider cultural differences more thoroughly when developing commonly used AI tools for higher education. These tools should consider the cultural distinctions between high-context and low-context cultures and be tailored to the specific cultural contexts of different countries.

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