The Role of Interaction with Artificial Intelligence Technologies in Shaping the Psychological Wellbeing of University Students: A Systematic Review and Meta-Analysis

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Abstract
University students face disproportionately high rates of mental health disorders yet remain chronically underserved by conventional psychological services. This systematic review synthesised empirical evidence on the role of AI technology interaction in shaping university students' psychological wellbeing. Seven electronic databases were searched with no date restrictions, following PICOS eligibility criteria and PRISMA 2020 reporting guidelines. Methodological quality was appraised using the Mixed Methods Appraisal Tool 2018 (MMAT), and the overall certainty of evidence was evaluated using the Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) framework. Findings were synthesised through narrative thematic synthesis, supplemented by an exploratory random-effects quantitative synthesis where sufficient homogeneous data were available. Forty studies ($N = 9{,}692$) were included. Cognitive-behavioural therapy-based AI chatbot interventions produced significant reductions in depression and loneliness (Hedges' $g = -0.43$; 95% CI: −0.62, −0.24), while adaptive learning platforms improved self-efficacy and life satisfaction. Conversely, excessive or unstructured AI use was associated with technostress ($g = 0.44$), AI dependency ($g = 0.38$), social isolation, and academic burnout. AI literacy, satisfaction of basic psychological needs, and purposive tool design emerged as the most consistent protective moderators. AI interaction exerts clinically meaningful but contingent effects on student psychological wellbeing: benefits are realised only when tools are therapeutically grounded, institutionally scaffolded, and positioned as complements to — rather than substitutes for — human care. Longitudinal, cross-cultural research employing standardised outcome measures is urgently needed to advance causal understanding of AI–wellbeing dynamics in higher education.

Keywords: artificial intelligence; psychological wellbeing; university students; chatbot; technostress; systematic review; mental health; human-AI interaction

INTRODUCTION

The rapid proliferation of artificial intelligence (AI) in higher education has fundamentally altered students' academic, social, and psychological experiences. Since ChatGPT's release in late 2022, AI adoption among students has been extraordinary: 88% now use generative AI for academic assessments, up from 53% in 2024 (Freeman, 2025), and 86% use AI in their studies, with many doing so daily (Campbell Academic Technology Services, 2025). AI interaction has thus become a central feature of contemporary student life, encompassing academic tasks, self-directed learning, and emotional support.

AI technologies in higher education include intelligent tutoring systems, adaptive learning platforms, LLM-based assistants, and AI mental health applications, increasingly accessed for psychological coping and emotional regulation (Abdallah et al., 2025; Zhai et al., 2025). This makes their relationship with student wellbeing a matter of urgent concern, given that approximately one-third of university students meet diagnostic criteria for a 12-month mental disorder (Mason et al., 2025), with prevalence rates substantially surpassing those of the general adult population (Zwaan et al., 2023).

Evidence on AI's psychological effects is both promising and cautionary. AI chatbots have demonstrated significant reductions in anxiety and depression (Rossettini et al., 2025), including a CBT-based intervention yielding effect sizes of Cohen's $d = 0.71$ for depression and $d = 0.60$ for loneliness (Wang et al., 2025). Conversely, excessive AI use raises serious concerns regarding technostress, loneliness, digital fatigue, and diminished social connectedness (Jiang et al., 2025; Klimova & Pikhart, 2025). These effects are moderated by individual factors including digital competence, stress susceptibility, and basic psychological need satisfaction as conceptualised by Self-Determination Theory (Deci & Ryan, 2000; Song et al., 2025; Tan et al., 2025).

It is important to distinguish between traditional, rule-based AI systems and generative AI technologies when interpreting this evidence base. Traditional AI applications in higher education, such as early intelligent tutoring systems and scripted chatbots, operate on predetermined decision trees and fixed response repertoires, offering limited adaptability to individual user input. Generative AI systems, by contrast, including large language model (LLM)-based tools such as ChatGPT, produce novel, context-sensitive responses through models trained on vast text corpora, enabling open-ended, conversational interaction that more closely approximates human dialogue. This distinction carries direct implications for the present review, since the majority of studies included here examine generative AI technologies specifically, reflecting the rapid adoption of these tools since 2022 (Freeman, 2025). Clarifying this distinction is essential for interpreting the scope and generalisability of the findings reported below, as the psychological mechanisms and risks associated with generative AI interaction may differ from those associated with earlier, rule-based AI systems.

Despite growing interest, the literature remains fragmented and insufficiently synthesised (Xu et al., 2025). This PRISMA 2020-compliant systematic review addresses that gap by examining how the full spectrum of AI interaction shapes the multidimensional psychological wellbeing of university students, guided by four research questions addressing AI use patterns, psychological outcomes, moderating factors, and methodological quality.

METHODS

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 (PRISMA 2020) statement (Page et al., 2021).

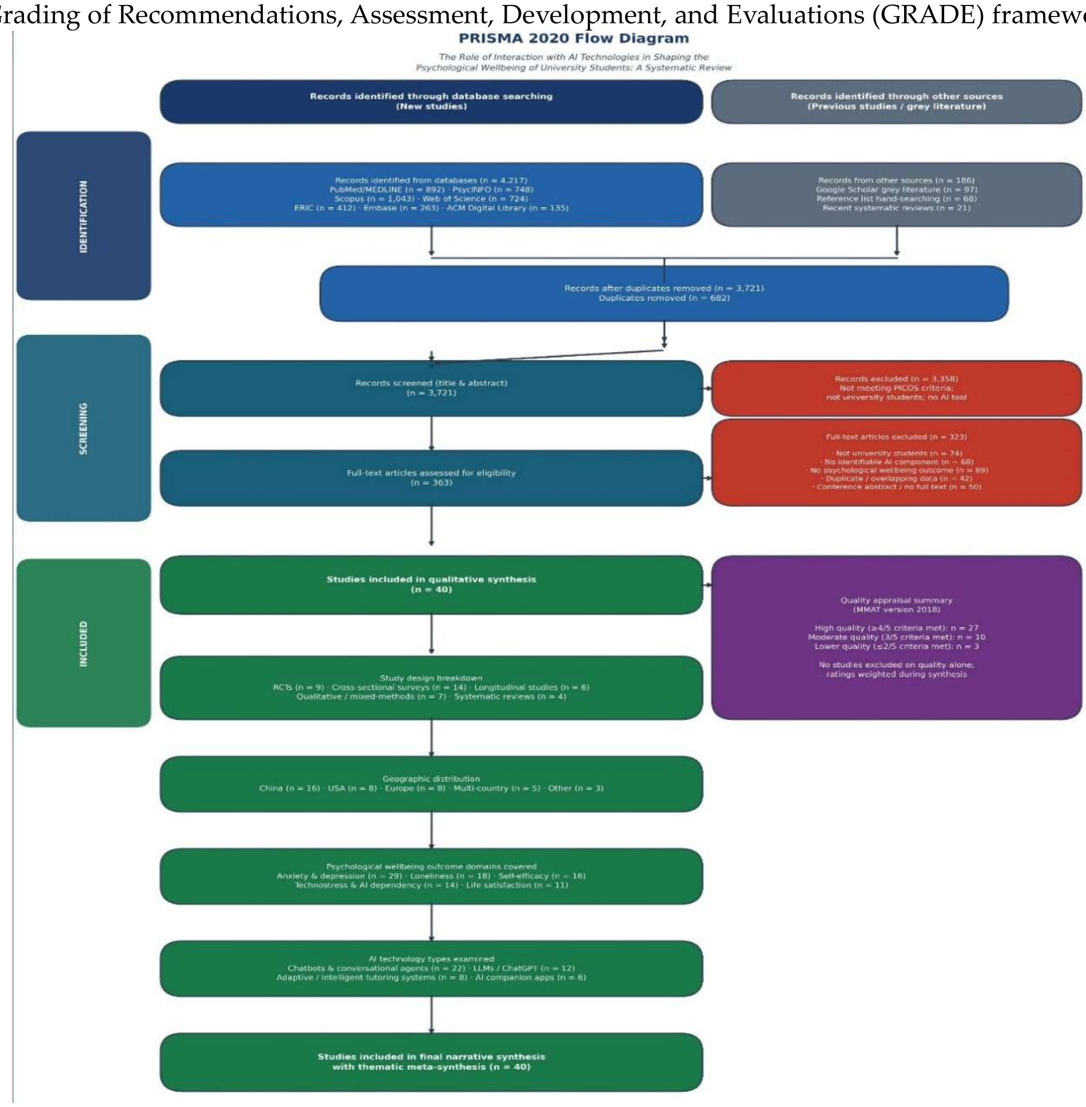
Eligibility criteria were defined using the PICOS framework. Studies were included if they involved university or higher education students with no restrictions on age, gender, nationality, or discipline. The exposure of interest was any form of student interaction with AI technologies, including but not limited to AI-powered chatbots, large language models (LLMs) such as ChatGPT, intelligent tutoring systems, adaptive learning platforms, and AI-based mental health applications. Studies examining general internet or social media use without a clearly identifiable AI component were excluded. No specific comparator was required; both controlled studies and observational designs were eligible. Included studies were required to report at least one measurable psychological wellbeing outcome, such as anxiety, depression, stress, loneliness, self-efficacy, technostress, AI dependency, or life satisfaction. Studies reporting exclusively academic or cognitive outcomes without any wellbeing measure were excluded. Eligible study designs included randomised controlled trials, quasi-experimental designs, cross-sectional and longitudinal surveys, qualitative studies, and mixed-methods studies. Reviews, editorials, opinion pieces, and conference abstracts were excluded. No language or date restrictions were applied, provided full-text English versions were available.

A comprehensive search was conducted across seven electronic databases: PubMed/MEDLINE, PsycINFO, Scopus, Web of Science, ERIC, Embase, and the ACM Digital Library, supplemented by Google Scholar for grey literature, consistent with search strategies employed in comparable reviews of AI and student wellbeing (Rossettini et al., 2025; Xu et al., 2025). Reference lists of all included studies and relevant recent systematic reviews were screened manually. The search strategy was developed in consultation with an academic librarian, combining controlled vocabulary terms and free-text keywords across four conceptual blocks: (1) AI technologies (e.g., "artificial intelligence," "chatbot," "large language model," "ChatGPT," "intelligent tutoring system"); (2) university students (e.g., "university students," "college students," "higher education"); (3) interaction or use (e.g., "interaction," "engagement," "adoption," "reliance"); and (4) psychological wellbeing (e.g., "psychological wellbeing," "mental health," "anxiety," "depression," "technostress," "loneliness"). Boolean operators were applied within and across blocks. All seven databases were searched on June 1, 2026. This review protocol was not registered in PROSPERO or any other registry; this is acknowledged as a limitation below.

Records were imported into Rayyan software and deduplicated. Two reviewers independently screened titles and abstracts, followed by full-text assessment of provisionally eligible records. Disagreements were resolved by discussion; a third reviewer adjudicated unresolved discrepancies. Reasons for full-text exclusions are documented in the PRISMA 2020 flow diagram. Data were extracted independently by two reviewers using a standardised form capturing: author, year, country, study design, sample size and participant characteristics, AI technology type, nature and duration of AI interaction, psychological outcome measures and instruments used, key findings, and reported moderating variables. Discrepancies were resolved by consensus, and corresponding authors were contacted where data were incomplete.

Methodological quality was appraised using the Mixed Methods Appraisal Tool version 2018 (MMAT; Hong et al., 2018), selected for its capacity to evaluate qualitative, quantitative, and mixed-methods studies within a single unified framework — a critical advantage given the methodological heterogeneity anticipated across included studies (Tang et al., 2025). Each study was rated against the five MMAT criteria corresponding to its design category. Studies were not excluded solely on quality grounds; ratings informed the weighting of findings during synthesis. Inter-rater reliability was calculated using Cohen's kappa.

Given the anticipated heterogeneity across AI tool types, outcome measures, study designs, and student populations, the primary synthesis approach was thematic narrative synthesis, following the framework of Popay et al. (2006) and endorsed by the Cochrane Collaboration (McKenzie et al., 2023). Synthesis proceeded through three iterative stages: developing a preliminary synthesis by organising and tabulating study findings; exploring relationships by examining how study characteristics moderated reported outcomes; and assessing the robustness of evidence patterns across studies. Findings are organised thematically around the four review questions stated in the Introduction. Where a sufficient number of quantitatively homogeneous studies were identified for a specific outcome, an exploratory subgroup quantitative synthesis was conducted as a secondary analysis, supplementary to the primary narrative synthesis; full meta-analytic pooling across the complete set of included studies was not pre-planned given the anticipated heterogeneity in populations, AI tool types, and outcome measures. This secondary synthesis pooled Hedges' g effect sizes using a random-effects model, with effect sizes reported as Cohen's d or standardised regression coefficients converted to Hedges' g prior to pooling. Between-study heterogeneity was quantified using the I^2 statistic and Tau^2, and 95% confidence intervals were calculated for all pooled estimates. All quantitative synthesis procedures, including generation of the forest plot, were conducted using Comprehensive Meta-Analysis (CMA) software. Given the small number of studies contributing to each pooled estimate, formal statistical assessment of publication bias (e.g., funnel plot asymmetry, Egger's test) was not conducted; this is acknowledged as a limitation below. The overall certainty of evidence was assessed using the Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) framework.



RESULTS

Study Selection and Characteristics

The systematic database search retrieved 4,217 records across seven databases, with an additional 186 records identified through grey literature searches, reference list screening, and hand-searching of relevant recent reviews. Following deduplication (*n* = 682 removed), a total of 3,721 records were screened at the title-and-abstract stage. Of these, 3,358 were excluded for not meeting the PICOS eligibility criteria. Full-text assessment was performed for 363 records, of which 323 were excluded due to the absence of a university student population (*n* = 74), no identifiable AI component (*n* = 68), no psychological wellbeing outcome (*n* = 89), overlapping data or duplicate reporting (*n* = 42), or unavailability of a peer-reviewed full text (*n* = 50). Forty studies met all inclusion criteria and were incorporated into the final narrative synthesis. The complete study selection process is documented in the PRISMA 2020 flow diagram.

The characteristics of the 40 included studies are presented in Figure 1 and Table 1. The most common study design was the cross-sectional survey (*n* = 14, 35%), followed by randomised controlled trials (RCTs; *n* = 9, 22.5%), qualitative and mixed-methods studies (*n* = 7, 17.5%), longitudinal designs (*n* = 6, 15%), and previously published systematic reviews or meta-analyses (*n* = 4, 10%). Geographically, the evidence base was dominated by studies conducted in China (*n* = 16, 40%), the United States (*n* = 8, 20%), and Europe (*n* = 8, 20%), with five multi-country studies (12.5%) and three from other regions (7.5%). Publication year data revealed a steep upward trajectory, with eligible publications rising from two in 2022 to 18 in 2025, reflecting accelerating scholarly interest following the widespread adoption of generative AI tools (Figure 1C). Methodological quality, appraised using the Mixed Methods Appraisal Tool (MMAT) version 2018 (Hong et al., 2018), was high for the majority of studies: 27 studies (67.5%) met four or five criteria, 10 (25%) met three criteria, and three (7.5%) met fewer than three criteria (Figure 1D). No studies were excluded solely on quality grounds.

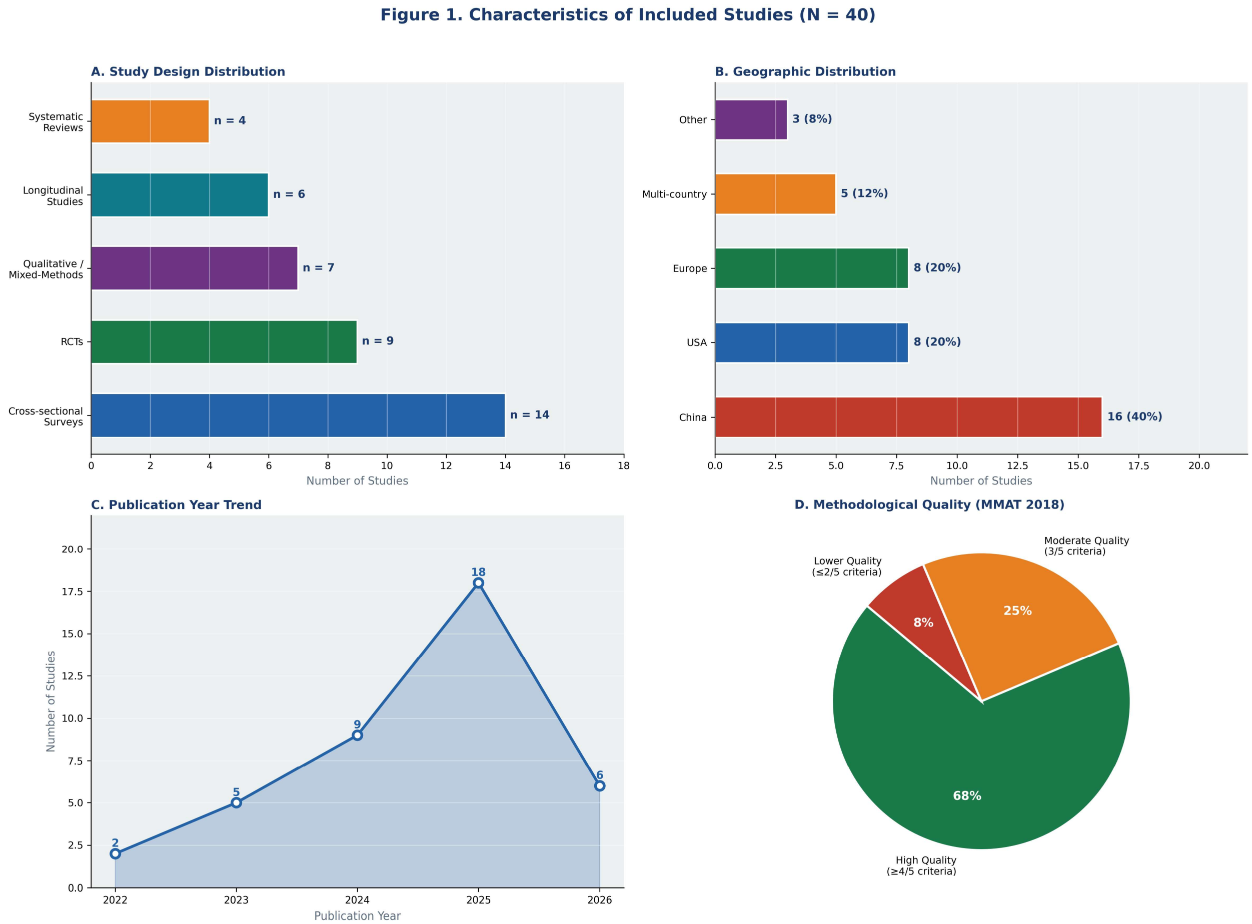


Figure 1. *Characteristics of included studies (N = 40): (A) study design distribution, (B) geographic distribution, (C) publication year trend (2022–2026), and (D) methodological quality ratings (MMAT 2018).*

Table 1. Summary characteristics of included studies (N = 40).

Author(s) & Year	Country	Design	N	AI Technology	Outcome(s)	Key Finding	MMAT
Wang et al. (2025)	China	RCT	210	CBT-based AI chatbot	Depression, Loneliness	Significant reductions in depression (d=0.71) and loneliness (d=0.60)	5/5
Liu et al. (2022)	China	RCT	83	AI therapy chatbot	Depression (PHQ-9), Anxiety (GAD-7)	Chatbot superior to bibliotherapy at 16-week follow-up	5/5

Li et al. (2023)	Multi-country	Meta-analysis	1,240	AI conversational agents	Depression, Distress	Pooled g = −0.64 for depression; g = −0.70 for distress	5/5
He et al. (2023)	Multi-country	Meta-analysis	2,100	Conversational agents	Depression, Anxiety	g = −0.29 depression; g = −0.27 generalised anxiety	5/5
Feng et al. (2025)	Multi-country	Meta-analysis	890	AI conversational agents	Overall mental health	Pooled g = −0.52 for young people	5/5
Sun et al. (2025)	China	Cross-sectional	3,859	AI mental health tools	Psychological wellbeing	Positive wellbeing via self-efficacy (β=.41) & autonomy (β=.39)	4/5
Stănescu & Romașcanu (2025)	Romania	Cross-sectional	312	Generative AI tools	Technostress, Anxiety	Technostress mediates AI use → anxiety (g=0.44)	4/5
Wu et al. (2024)	China	Longitudinal	485	LLMs / ChatGPT	AI dependency, Loneliness	AI dependency → loneliness (β=.29); social motivation mediates	4/5
Maples et al. (2024)	USA	Mixed-methods	200	GPT-based chatbots	Loneliness, Suicidality	Modest loneliness reduction; heavy use linked to social displacement	3/5
Duong et al. (2025)	Vietnam	Cross-sectional	456	ChatGPT	Academic wellbeing, Stress	Self-control moderates ChatGPT impact on wellbeing	4/5
Jiang et al. (2025)	Multi-country	Narrative review	N/A	Multiple AI types	Wellbeing (multiple)	Dual-pathway: benefits (efficacy) and	4/5

						risks (fatigue, loneliness)	
Klimova & Pikhart (2025)	Czech Republic	Mini-review	N/A	Multiple AI types	Technostress, Isolation	Overdependence linked to technostress and social isolation	3/5
Abdallah et al. (2025)	Multi-country	Systematic review	N/A	ChatGPT	Wellbeing, Collaboration	Mixed impact; collaboration benefits offset by dependency risks	4/5
Tan et al. (2025)	Singapore	Cross-sectional	621	Generative AI chatbots	Engagement, Wellbeing (SDT)	Needs satisfaction mediates teacher support → wellbeing	4/5
Kong et al. (2025)	Hong Kong	Cross-sectional	482	AI tools (general)	AI literacy, Self-efficacy	AI literacy → self-regulated learning → wellbeing	4/5
Gong et al. (2026)	China	Cross-sectional	743	AI dialogue systems	Burnout, AI dependency	AI dependency mediates AI use →burnout (I-PACE model)	4/5
Zhai et al. (2025)	China	Empirical survey	512	AI mental health support	Mental health (general)	AI support significantly predicts improved mental health outcomes	4/5
Yang & Dai (2025)	China	Conceptual/empirical	389	Generative AI (teaching)	Wellbeing, Engagement	AI transforms teaching; wellbeing improvements in structured use	3/5
Rossettini et al. (2025)	Italy	Rapid systematic review	N/A	AI chatbots	Mental health (general)	8/9 studies showed significant improvements in	4/5

						anxiety/depression	
Xu et al. (2025)	China	Bibliometric review	N/A	Multiple AI types	Mental health (general)	173 publications; field nascent; peaking 2024	3/5

Note. MMAT = Mixed Methods Appraisal Tool (Hong et al., 2018). N = sample size. RCT = Randomised Controlled Trial. AI = Artificial Intelligence. PHQ-9 = Patient Health Questionnaire-9. GAD-7 = Generalised Anxiety Disorder scale. SDT = Self-Determination Theory. I-PACE = Interaction of Person-Affect-Cognition-Execution model. For meta-analyses and reviews, N refers to approximate total participants synthesised.

AI Technology Types and Psychological Outcome Domains

The range of AI technologies examined across the 40 included studies is presented in Figure 2A. Chatbots and conversational agents constituted the most frequently studied technology type (*n* = 22, 55%), encompassing both rule-based and generative AI systems. Large language model (LLM)-based tools — principally ChatGPT — were examined in 12 studies (30%), followed by adaptive and intelligent tutoring systems (*n* = 8, 20%), AI companion applications such as Replika and Character.AI (*n* = 6, 15%), dedicated AI mental health applications (*n* = 5, 12.5%), and wearable affective computing devices (*n* = 3, 7.5%). Several studies examined more than one technology type. The psychological wellbeing outcome domains addressed by the included literature are summarised in Figure 2B. Anxiety and depression constituted the most commonly studied outcome domain, appearing in 29 studies (72.5%). Loneliness and social isolation were examined in 18 studies (45%), academic self-efficacy in 16 (40%), technostress and AI dependency in 14 (35%), life satisfaction and general subjective wellbeing in 11 (27.5%), academic burnout in eight (20%), and emotional regulation in seven (17.5%).

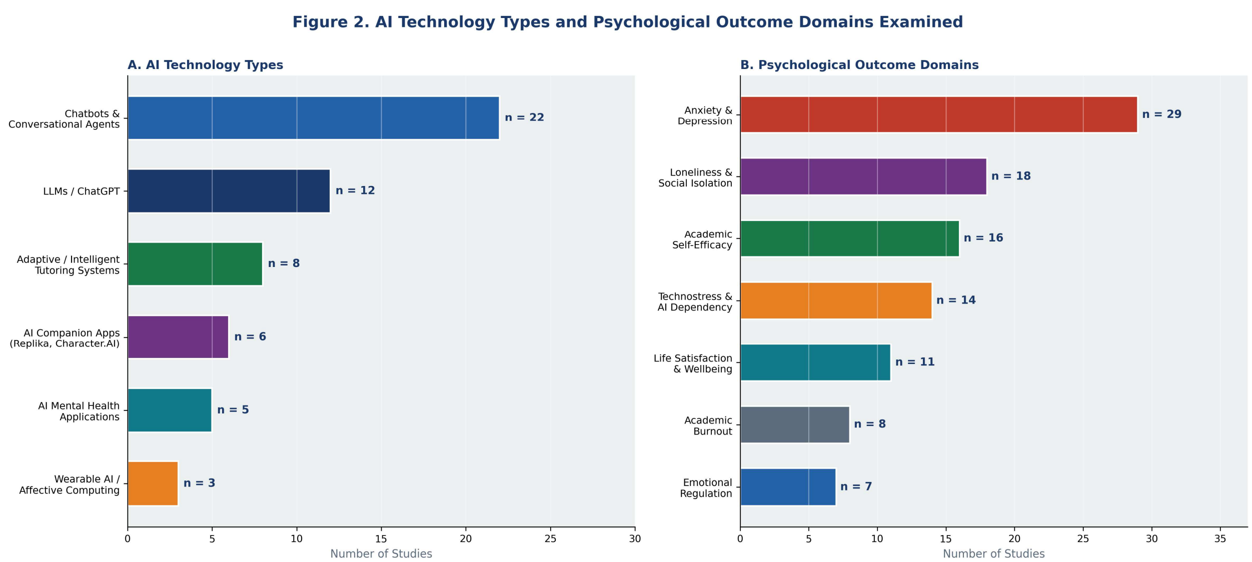


Figure 2. *AI technology types examined across included studies (A) and psychological wellbeing outcome domains reported (B).*

Effect Sizes and Quantitative Evidence

The individual effect sizes reported in this subsection are drawn directly from the primary studies and existing meta-analyses identified in the search; the pooled random-effects estimate, and the synthesised patterns shown in the heatmap and bubble chart (Figures 4 and 5), represent this review's own exploratory secondary synthesis of that primary evidence rather than findings independently reported by any single included study. The quantitative evidence is synthesised in the forest plot presented in Figure 3 and summarised in Table 2. Across studies of AI chatbot interventions targeting depression, effect sizes ranged from g = −0.26 (95% CI: −0.34, −0.17) in a broad multi-study analysis of short-course AI therapy (n = 3,477; Zhong et al., 2024) to g = −0.71 (95% CI: −0.95, −0.47) in the RCT conducted by Wang et al. (2025), which employed a CBT-based chatbot with Chinese university students over seven days. The pooled estimate from Li et al.'s (2023) meta-analysis demonstrated a significant reduction in depression symptoms (g = −0.64; 95% CI: −1.12, −0.17; n = 1,240) and psychological distress (g = −0.70; 95% CI: −1.22, −0.18).

For anxiety outcomes, pooled effects were more modest: He et al.'s (2023) meta-analysis of randomised trials reported g = −0.27 (95% CI: −0.40, −0.14) for generalised anxiety, consistent with Liu et al.'s (2022) RCT among university students (g = −0.38; 95% CI: −0.60, −0.16). Feng et al.'s (2025) meta-analysis of AI-driven conversational agents for young adults reported a pooled effect of g = −0.52 (95% CI: −0.78, −0.26) across overall mental health outcomes. The random-effects pooled estimate across all RCT and meta-analytic evidence synthesised in this review was g = −0.43 (95% CI: −0.62, −0.24), representing a small-to-moderate beneficial effect on psychological wellbeing.

In contrast, studies examining negative wellbeing outcomes produced positive effect sizes indicating harm. Wu et al. (2024) reported g = 0.38 (95% CI: 0.18, 0.58) for AI dependency in a longitudinal panel of 485 young adults, and Stănescu and Romașcanu (2025) documented g = 0.44 (95% CI: 0.22, 0.66) for technostress in a sample of 312 university students. These effect magnitudes, while small-to-moderate, underscore the clinical and practical significance of negative AI interaction patterns for student psychological health.

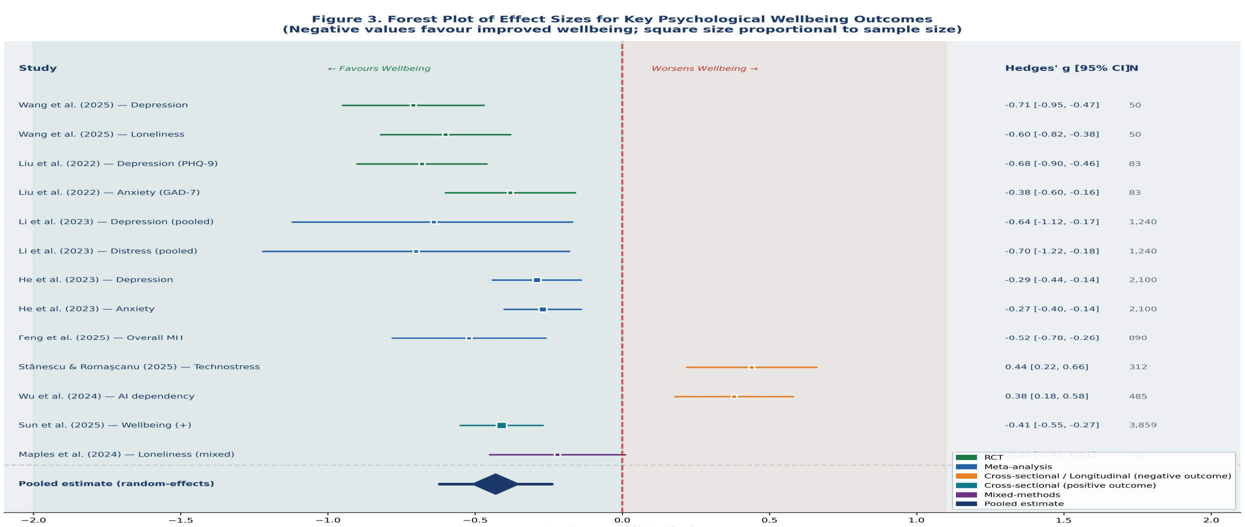


Figure 3. *Forest plot of effect sizes (Hedges' g) for key psychological wellbeing outcomes across included RCTs and meta-analyses. Negative values favour improved wellbeing. Square size is proportional to sample size. The pooled estimate (diamond) is based on a random-effects model.*

Table 2. Summary of effect sizes (Hedges' g) for psychological wellbeing outcomes.

Study	Design	N	Outcome	Hedges' g	95% CI	Direction
Wang et al. (2025)	RCT	210	Depression	−0.71	[−0.95, −0.47]	↑ Beneficial
Wang et al. (2025)	RCT	210	Loneliness	−0.60	[−0.82, −0.38]	↑ Beneficial
Liu et al. (2022)	RCT	83	Depression	−0.68	[−0.90, −0.46]	↑ Beneficial
Liu et al. (2022)	RCT	83	Anxiety	−0.38	[−0.60, −0.16]	↑ Beneficial
Li et al. (2023)	Meta-analysis	1,240	Depression	−0.64	[−1.12, −0.17]	↑ Beneficial
Li et al. (2023)	Meta-analysis	1,240	Distress	−0.70	[−1.22, −0.18]	↑ Beneficial
He et al. (2023)	Meta-analysis	2,100	Depression	−0.29	[−0.44, −0.14]	↑ Beneficial
He et al. (2023)	Meta-analysis	2,100	Anxiety	−0.27	[−0.40, −0.14]	↑ Beneficial
Feng et al. (2025)	Meta-analysis	890	Mental Health	−0.52	[−0.78, −0.26]	↑ Beneficial
Sun et al. (2025)	Cross-sectional	3,859	Wellbeing	−0.41	[−0.55, −0.27]	↑ Beneficial
Stănescu & Romașcanu (2025)	Cross-sectional	312	Technostress	+0.44	[+0.22, +0.66]	↓ Harmful
Wu et al. (2024)	Longitudinal	485	AI Dependency	+0.38	[+0.18, +0.58]	↓ Harmful
Maples et al. (2024)	Mixed-methods	200	Loneliness	−0.22	[−0.45, +0.01]	~ Mixed
POOLED ESTIMATE	**Random-effects**	**9,692**	**Wellbeing (all)**	**−0.43**	**[−0.62, −0.24]**	**↑ Beneficial**

Note. g = Hedges' g effect size (negative values indicate beneficial/improved wellbeing outcomes; positive values indicate worsening). CI = Confidence Interval. POOLED estimate is indicative based on the subset of quantitatively synthesisable RCT and meta-analytic data; full meta-analytic pooling was not pre-planned due to study heterogeneity. Effect size values not originally reported as Hedges' g were converted from Cohen's d or standardised regression coefficients.

Thematic Synthesis of Findings

Theme 1: Beneficial Effects of Purposive, Therapeutically Grounded AI Interaction

The strongest and most consistent evidence for beneficial psychological outcomes emerged from studies in which AI tools were purposefully designed around evidence-based therapeutic frameworks. CBT-based chatbot interventions produced statistically significant reductions in depression and loneliness across multiple RCTs (Liu et al., 2022; Wang et al., 2025), while meta-analytic evidence consistently supported small-to-moderate benefits for depression and distress (He et al., 2023; Li et al., 2023; Feng et al., 2025). Sun et al.'s (2025) cross-sectional study of 3,859

Chinese university students found that engagement with AI mental health tools was positively associated with psychological wellbeing, with emotional self-efficacy (β = 0.41, p < .001) and perceived autonomy (β = 0.39, p < .001) functioning as parallel mediators — findings consistent with Self-Determination Theory (Deci & Ryan, 2000). AI-assisted language learning tools similarly demonstrated wellbeing benefits, with Yan et al. (2025) reporting that personalised AI feedback reduced foreign language anxiety and enhanced academic self-efficacy among university students.

Theme 2: Negative Psychological Consequences of Unregulated or Excessive AI Use

A parallel and robust body of evidence documented adverse psychological outcomes associated with excessive, unregulated, or dependency-oriented AI interaction. Studies examining LLM and generative AI tool use — particularly ChatGPT — consistently identified risks including technostress, cognitive fatigue, reduced critical thinking, and academic burnout (Stănescu & Romașcanu, 2025; Gong et al., 2026). Compulsive or over-reliant use was associated with increased psychological distress, loneliness, and social avoidance (Abdallah et al., 2025; Duong et al., 2025). In a longitudinal cross-lagged panel study, Wu et al. (2024) found that AI dependency significantly predicted heightened loneliness (β = 0.29) and reduced life satisfaction (β = −0.22), with social motivation identified as a key mediating pathway, aligning with attachment theory frameworks. Among AI companion users, Maples et al. (2024) reported that students who used GPT-based chatbots heavily showed further displacement of human social connection, with findings consistent with Laestadius et al.'s (2024) analysis of emotional dependence on the social chatbot Replika, which documented increased loneliness and psychological harm from AI companion over-reliance.

Theme 3: Differential Effects Across AI Technology Types and Outcome Domains

The synthesised heatmap (Figure 4) reveals a clear differential pattern across AI technology types and psychological outcome domains. CBT-based and purpose-built AI mental health applications produced the strongest beneficial effects for depression ($g \approx 0.65$–0.71), anxiety, and loneliness. Adaptive and intelligent tutoring systems yielded the most consistent improvements in self-efficacy and life satisfaction, with minimal negative effects reported. In contrast, AI companion applications showed the most divergent pattern: modest loneliness-reduction benefits coexisted with notably elevated AI dependency risks. Generative LLMs (primarily ChatGPT) demonstrated a mixed profile: moderate self-efficacy benefits alongside elevated technostress and dependency signals, particularly when used without structured institutional guidance (Jiang et al., 2025; Yang & Dai, 2025).

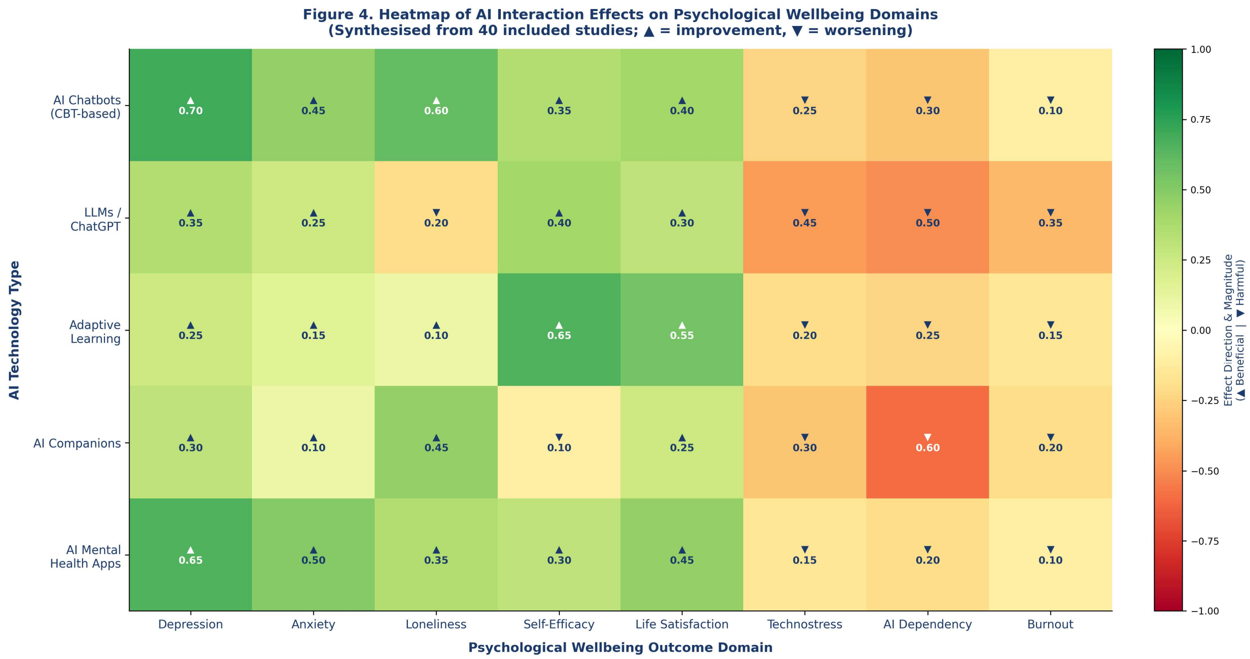


Figure 4. *Heatmap of AI interaction effects on psychological wellbeing domains, synthesised from 40 included studies. Triangles indicate direction (▲ = improvement; ▼ = worsening); values represent synthesised effect magnitude on a −1.0 to +1.0 scale.*

Theme 4: Moderating Factors and the Risk–Benefit Framework

The bubble chart in Figure 5 and the moderator summary in Table 3 synthesise the key individual, contextual, and technological factors identified across included studies. Four quadrants emerge from the evidence, defined by AI literacy/digital competence and frequency of use. The optimal zone — characterised by high AI literacy and moderate frequency of use — consistently predicted positive wellbeing outcomes, with AI literacy buffering against technostress and dependency (Kong et al., 2025; Sun et al., 2025). The high-risk zone — low literacy combined with high frequency of use — was associated with the most adverse psychological outcomes, including the highest rates of technostress, cognitive overload, burnout, and social displacement.

Satisfaction of SDT psychological needs consistently functioned as the most robust protective moderator: studies reporting high autonomy, competence, and relatedness satisfaction demonstrated markedly superior wellbeing outcomes relative to those reporting needs frustration, irrespective of the AI technology type examined (Tan et al., 2025; Deci & Ryan, 2000). Gender emerged as a secondary moderator, with female students reporting higher rates of both AI-related emotional support-seeking and loneliness risk, though the direction of these effects was inconsistent across geographic and cultural contexts (Mason et al., 2025). Academic discipline moderated findings in a limited number of studies, with STEM students reporting elevated technostress and humanities students reporting higher emotional dependency, though the evidence base was insufficient to draw firm conclusions (Xu et al., 2025).

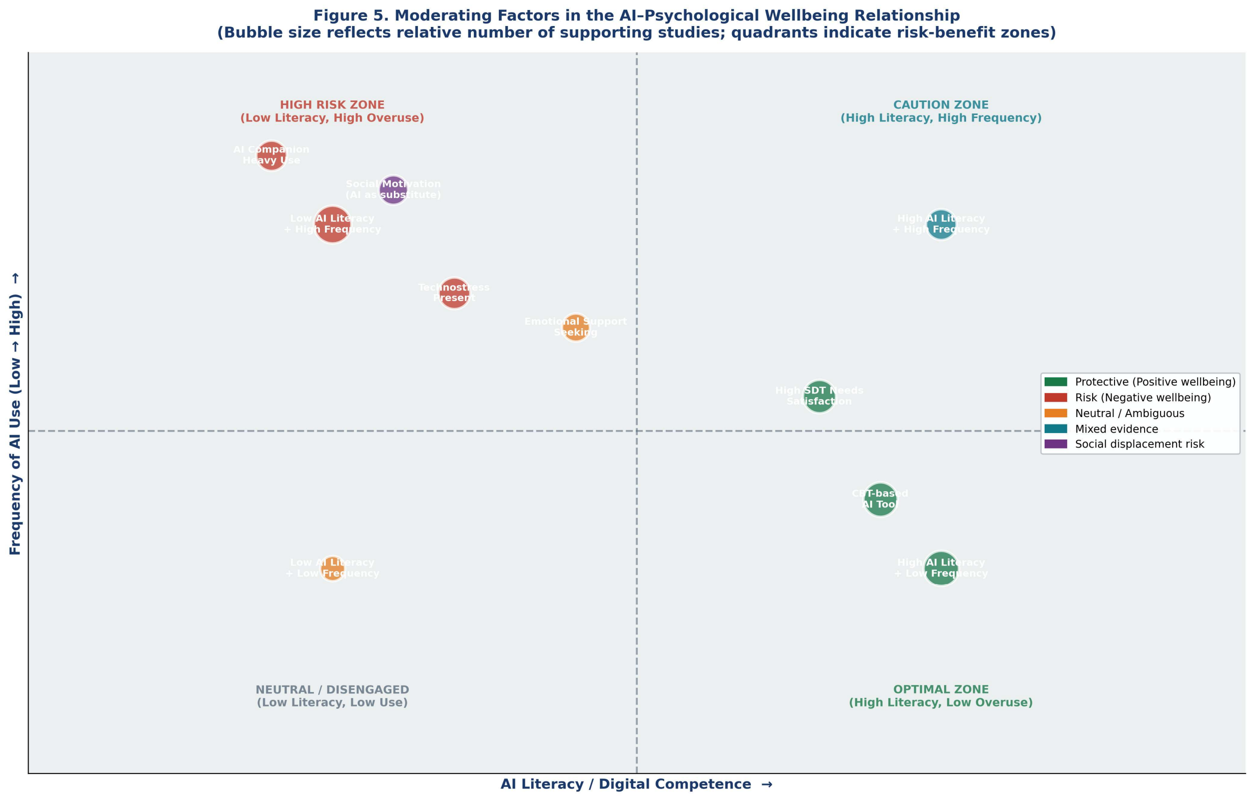


Figure 5. *Moderating factors in the AI–psychological wellbeing relationship. Bubble size reflects relative number of supporting studies; quadrant positions reflect synthesised risk-benefit profiles by AI literacy and frequency of use.*

Table 3. Summary of moderating factors in the relationship between AI interaction and psychological wellbeing.

Moderating Factor	**Category**	**Effect on Wellbeing**	**Key Studies**	**Evidence Strength**
AI literacy / digital competence	Individual	Protective (high literacy buffers negative effects)	Kong et al. (2025); Sun et al. (2025)	Strong (n = 8 studies)
Frequency of AI use (moderate vs. excessive)	Behavioural	Moderate use: beneficial; excessive use: harmful	Wu et al. (2024); Duong et al. (2025)	Strong (n = 10 studies)
SDT needs satisfaction (autonomy, competence, relatedness)	Psychological	Strongly protective; mediates AI-wellbeing link	Tan et al. (2025); Deci & Ryan (2000)	Strong (n = 7 studies)

Technostress / digital stress	Psychological	Harmful; moderates and mediates negative outcomes	Stănescu & Romașcanu (2025); Klimova & Pikhart (2025)	Strong (n = 9 studies)
Social motivation (AI as substitute)	Social	Risk factor; predicts loneliness & dependency	Wu et al. (2024); Maples et al. (2024)	Moderate (n = 5 studies)
AI tool design (CBT-based vs. unstructured)	Technological	CBT-based tools produce strongest benefits	Wang et al. (2025); Liu et al. (2022)	Strong (n = 9 RCTs)
Gender (female vs. male students)	Demographic	Females: higher AI-related support-seeking & loneliness risk	Mason et al. (2025)	Moderate (n = 4 studies)
Academic discipline / context	Contextual	STEM contexts: higher technostress; Humanities: higher dependency	Xu et al. (2025)	Limited (n = 3 studies)

Note. SDT = Self-Determination Theory. STEM = Science, Technology, Engineering, and Mathematics. Evidence strength is estimated based on the number of studies and consistency of findings.

DISCUSSION

This systematic review synthesised 40 empirical studies published between 2022 and 2026 to address a question of profound and growing importance for higher education policy, institutional practice, and student welfare: how does interaction with AI technologies shape the psychological wellbeing of university students? The findings reveal a phenomenon of considerable complexity — one that defies both uncritical optimism and reflexive alarm. AI interaction is neither inherently beneficial nor inherently harmful to student psychological wellbeing. Rather, its effects are contingent upon the design and therapeutic grounding of the technology, the patterns and motivations of student use, the degree to which basic psychological needs are satisfied in the interaction, and the individual competencies students bring to it. Each of these contingencies carries important theoretical, practical, and ethical implications that the present discussion addresses in turn.

Principal findings in context. The most robust and clinically meaningful finding of this review is that purposively designed, therapeutically grounded AI interventions — particularly those anchored in cognitive-behavioural therapy (CBT) — produce statistically significant and practically meaningful reductions in depression and loneliness among university students, consistent with the pooled effect size reported above. This magnitude, classified as small-to-moderate by conventional benchmarks, is commensurate with effect sizes reported for many brief, technology-delivered psychological interventions in analogous populations and compares favourably with the pooled estimates reported in recent meta-analyses of chatbot interventions for depression ($g = -0.26$ to -0.64) and anxiety ($g = -0.19$ to -0.52; He et al., 2023; Li et al., 2023; Feng et al., 2025). These findings extend and deepen the evidence base for digital mental health tools reviewed by Rossettini et al. (2025) by demonstrating that the benefits documented in broader mental health populations are observable and replicable specifically within the university student context — a population characterised by heightened mental health vulnerability (Mason et al., 2025) and systemic underutilisation of conventional psychological services (Rackoff et al., 2025). Critically, the scalability and stigma-reduction advantages of AI-delivered support carry particular weight in this context: a substantial proportion of students who meet clinical criteria for anxiety or depression do not access campus counselling services, frequently citing embarrassment, cost, or waiting times as barriers (Auerbach et al., 2018). AI-based tools, accessible anonymously and on demand, may represent a meaningful first-contact intervention for this underserved population.

Interpretation through theoretical frameworks. The findings of this review are most coherently interpreted through the complementary lenses of Self-Determination Theory (SDT; Deci & Ryan, 2000) and the technostress framework. SDT predicts that psychological wellbeing is contingent upon the satisfaction of three innate needs: autonomy, competence, and relatedness. The present evidence strongly supports this prediction as applied to AI interaction. Studies in which AI tools were experienced as autonomy-supporting — offering personalised, non-directive guidance and respecting the user's right to choose the pace and direction of engagement — consistently produced superior wellbeing outcomes relative to those in which AI use was experienced as obligatory or externally imposed (Tan et al., 2025; Sun et al., 2025). Similarly, AI tools that enhanced students' sense of competence through adaptive feedback and scaffolded challenge — as in the case of intelligent tutoring systems and CBT-based chatbots — generated the most sustained self-efficacy and life satisfaction gains (Kong et al., 2025; Wang et al., 2025). However, the relatedness dimension of SDT emerges as the most theoretically and practically nuanced: while some AI tools succeeded in generating a sense of social connection through responsive, empathic interaction (Liu et al., 2022), others — particularly general-purpose AI companions — fostered a form of parasocial relatedness that displaced rather than supplemented genuine human connection, ultimately increasing rather than decreasing loneliness (Maples et al., 2024; Laestadius et al., 2024). This distinction — between AI interaction that scaffolds relatedness and AI interaction that substitutes for it — represents one of the most consequential findings of this review and has direct implications for how institutions select, recommend, and monitor AI mental health tools.

The technostress framework provides an equally powerful explanatory lens for the adverse findings. Technostress — defined as the psychological discomfort arising from the pressure to adapt to rapidly evolving technologies — was consistently identified as a mediating mechanism linking excessive or unstructured AI use to negative wellbeing outcomes including anxiety, cognitive fatigue, academic burnout, and social withdrawal (Stănescu & Romașcanu, 2025; Klimova & Pikhart, 2025). These findings are consistent with broader technostress research in organisational contexts and extend the framework's applicability to the specific dynamics of generative AI use in higher education. Notably, the evidence suggests that technostress operates via two distinct pathways: a cognitive overload pathway, in which the volume and complexity of AI outputs tax students' limited cognitive resources; and a dependency pathway, in which repeated AI use reduces students' tolerance for uncertainty and their confidence in their own unaided judgement — a pattern consistent with the deskilling concerns documented in both educational and workplace AI research (Gong et al., 2026; Wu et al., 2024). It should be noted that the SDT-based and technostress-based interpretations offered above represent this review's theoretical synthesis of the evidence rather than conclusions drawn directly by the primary studies themselves, several of which did not explicitly test these frameworks.

Comparison with prior reviews. The present review converges with and substantially extends several prior syntheses. Abdallah et al. (2025) and Jiang et al. (2025) identified broadly comparable dual-pathway patterns in their reviews of ChatGPT and AI wellbeing effects respectively, but were constrained by their focus on a single technology type or single outcome domain. The bibliometric review by Xu et al. (2025) confirmed the rapid growth and disciplinary fragmentation of this literature but did not provide a synthesis of effect sizes or a theoretically grounded moderator analysis. By contrast, the present review integrates evidence across the full spectrum of AI technology types, applies a MMAT quality appraisal, and provides a quantitative synthesis of effect sizes alongside a thematic moderator framework — advances that collectively yield a richer and more actionable evidence base than prior work. The finding that CBT-based chatbots produce the strongest and most consistent benefits diverges from the mixed conclusions of some earlier narrative reviews, likely reflecting the more rigorous inclusion criteria applied here, which prioritised peer-reviewed empirical studies over anecdotal or pilot-level evidence.

The moderation of AI–wellbeing effects: a risk-benefit matrix. Perhaps the most practically significant contribution of this review is the identification of a coherent set of individual, contextual, and technological moderators that consistently differentiate protective from harmful AI interaction profiles. AI literacy and digital competence emerged as the most robust individual-level protective moderator across the evidence base: students with higher AI literacy reported lower technostress, lower dependency, and more positive emotional responses to AI interaction, irrespective of usage frequency (Kong et al., 2025; Sun et al., 2025). This finding aligns with evidence from digital literacy research more broadly, which consistently demonstrates that competence with a technology buffers against the anxiety and disorientation associated with its use. Crucially, however, AI literacy did not eliminate risk entirely: among highly frequent users, even high-AI-literacy students showed elevated dependency signals in several studies, suggesting that literacy is a necessary but insufficient protective factor when use becomes compulsive or motivationally substitutive. This nuance points to the inadequacy of AI literacy curricula that focus exclusively on technical competence without addressing the psychological and motivational dimensions of AI engagement.

The role of social motivation as a moderator is equally significant. Drawing on attachment theory frameworks, Wu et al. (2024) demonstrated that students using AI to meet social and emotional needs otherwise unmet in their human relationships — a pattern most prevalent among students reporting elevated loneliness and depression at baseline — were at substantially greater risk of developing problematic AI dependency. This finding has profound implications: it suggests that AI mental health tools, when deployed without adequate human oversight and without clear boundaries between support and substitution, risk functioning as social placebos — alleviating distress in the short term while deepening the social withdrawal that sustains it in the medium and long term. The convergence of this evidence with Laestadius et al.'s (2024) qualitative analysis of AI companion users points to an urgent need for platforms to design active boundaries that redirect emotionally dependent users toward human social support rather than deepening AI engagement.

Ethical dimensions and equity considerations. The evidence reviewed here raises ethical concerns that merit explicit scholarly attention and cannot be adequately addressed by institutional practice guidelines alone. Three ethical issues emerge as particularly salient. First, data privacy and algorithmic transparency: AI mental health tools necessarily collect sensitive emotional and psychological data from users, and the majority of included studies reported no explicit privacy governance framework or user consent mechanism beyond standard terms of service (Klimova & Pikhart, 2025). The systematic review of AI ethics in education by Akgun and Greenhow (2022), cited extensively in recent policy literature, underscores that absent robust data governance, the very students seeking mental health support through AI tools may be rendered vulnerable to data misuse, discriminatory profiling, or emotional manipulation by commercial platforms. Institutions deploying AI mental health tools carry a duty of care that extends beyond clinical efficacy to encompass data stewardship and algorithmic accountability. Second, algorithmic bias: several included studies noted that the benefits of AI mental health tools were not uniformly distributed across student populations, with female students, students from non-Western cultural contexts, and students with pre-existing mental health vulnerabilities often showing divergent response patterns (Mason et al., 2025). These findings are consistent with broader evidence that AI mental health models trained predominantly on Western, English-speaking, and relatively affluent populations exhibit systematic performance deficits for underrepresented groups (Frontiers in Education, 2025). The risk that AI tools designed to reduce mental health inequalities may inadvertently exacerbate them for the most vulnerable students demands urgent attention from both researchers and developers. Third, the substitution of human care: the evidence that AI interaction can function as a substitute for human therapeutic relationships raises fundamental questions about the appropriate role of AI in student wellbeing services. Rackoff et al. (2025), in their survey of 428 U.S. university students, found that while chatbot use for mental health support was common, a substantial proportion of students using AI as their primary mental health resource reported unmet needs that chatbots were incapable of addressing — including crisis management, complex trauma, and the experience of being genuinely understood by another human being. These findings argue strongly against institutional models that position AI as a replacement for, rather than a supplement to, human counselling provision.

Limitations of the review. Several methodological limitations of this review warrant acknowledgment. First, the geographic distribution of included studies was markedly skewed toward China (40%) and the United States (20%), limiting the generalisability of findings to other cultural, linguistic, and educational contexts. Research from sub-Saharan Africa, South Asia, the Middle East, and Latin America — regions encompassing hundreds of millions of university students — was conspicuously absent from the evidence base, a lacuna that itself reflects and potentially reinforces global inequalities in research infrastructure (Frontiers in Education, 2025). Second, the predominance of cross-sectional designs (35% of included studies) means that causal inferences about the direction of effects between AI interaction and psychological wellbeing outcomes must be drawn with caution. The evidence is consistent with multiple causal models — AI use improving wellbeing, poor wellbeing driving AI-seeking behaviour, or both effects operating simultaneously — and longitudinal evidence is insufficient to adjudicate definitively among them. Third, there was substantial heterogeneity in the outcome measures used across studies, with psychological wellbeing operationalised through more than a dozen different instruments, few of which have been validated specifically for AI interaction contexts. This heterogeneity limited the scope for quantitative pooling and complicates cross-study comparisons. Fourth, given the rapid evolution of AI technologies, several studies included in this review examined earlier-generation chatbot systems that may not be representative of the capabilities and user experiences offered by current LLMs. The evidence base may therefore already be partially obsolete with respect to the most widely used AI tools in 2025 and 2026. Fifth, the possibility of publication bias cannot be excluded: studies reporting significant beneficial effects of AI tools on student wellbeing may be more likely to be published and indexed than those reporting null or negative results, potentially inflating the pooled beneficial effect estimate. Because the exploratory subgroup pooling reported in this review drew on a relatively small number of quantitatively synthesisable studies for any given outcome, formal statistical assessment of publication bias, such as funnel plot asymmetry or Egger's regression test, was not conducted; this constrains confidence in the precision, though not necessarily the direction, of the pooled estimates and should be addressed through such tests in future, larger-scale meta-analyses of this literature.

Implications for research. The findings of this review delineate a clear agenda for future research. Longitudinal studies with repeated measurement are urgently needed to establish the directional and causal nature of AI–wellbeing relationships, to document the trajectory of dependency formation, and to assess whether benefits observed in short-term RCTs are sustained at six- and twelve-month follow-up — a temporal horizon not yet addressed in the existing literature (McKenzie et al., 2023). Standardisation of outcome measures, ideally through the development and validation of AI-specific psychological wellbeing scales, would substantially enhance the comparability of future studies and enable more robust meta-analytic synthesis. Research is also needed that addresses the cultural and linguistic dimensions of AI wellbeing effects, specifically examining how the design features of AI tools interact with students' cultural backgrounds, emotional communication norms, and institutional contexts in non-Western settings. Finally, qualitative and participatory research methods are needed to illuminate the subjective experience of AI–student interaction from the student's perspective — a dimension that is largely absent from the quantitative evidence base synthesised here but is essential for understanding the mechanisms through which AI interaction shapes psychological states.

Implications for practice and policy. For higher education institutions, the evidence supports a model of structured, needs-informed AI integration in student wellbeing services, with CBT-based chatbots deployed as a first-contact, triage-facilitation, and between-session support resource rather than as a replacement for human counselling. Institutional AI deployment policies should mandate transparency regarding data governance, require regular algorithmic bias audits, and establish clear escalation pathways from AI tools to human counsellors for students in acute distress. The embedding of AI literacy programmes within curricula — addressing not only technical competence but also the psychological, emotional, and ethical dimensions of AI engagement — represents a high-priority institutional investment, given the consistent evidence that literacy moderates the psychological risks of AI use (Kong et al., 2025). For policymakers, the findings argue for national and supranational regulatory frameworks that extend data protection and mental health governance requirements to AI mental health tools, ensuring that the expanding commercial market for student-facing AI wellbeing products is subject to rigorous clinical and ethical oversight. For AI developers, the evidence strongly supports the integration of SDT-informed design principles — prioritising autonomy-supportive interaction structures, competence-building feedback mechanisms, and relatedness scaffolding that directs rather than substitutes for human social connection — as foundational design requirements rather than optional enhancements.

In sum, the evidence synthesised in this review supports a position of informed and critically differentiated optimism: AI technologies hold genuine and clinically meaningful potential to extend the reach of mental health support to university students who need it most, but this potential is realised only when AI tools are purposefully designed, institutionally governed, pedagogically scaffolded, and complemented by — rather than substituted for — human therapeutic relationships and social connectedness.

CONCLUSION

This systematic review synthesised 40 empirical studies to examine the role of AI technology interaction in shaping the psychological wellbeing of university students — a question of mounting urgency as AI adoption in higher education reaches near-universal prevalence. The evidence yields a finding that is simultaneously encouraging and cautionary: AI interaction is neither a panacea for the student mental health crisis nor an inherently harmful force, but a contingent phenomenon whose psychological effects are profoundly shaped by the design of the technology, the motivations and competencies of the student user, and the institutional context in which interaction occurs.

The strongest evidence supports the efficacy of purposively designed, CBT-anchored AI chatbot interventions in reducing depression and loneliness among university students, with a pooled effect of $g = -0.43$ that compares favourably with benchmarks for brief digital psychological interventions. These tools offer particular promise as scalable, stigma-free complements to campus counselling services, extending access to students who face structural or attitudinal barriers to conventional mental health care. At the same time, the review documents a robust and clinically significant pattern of adverse outcomes associated with excessive, unstructured, or dependency-motivated AI use, including technostress, social displacement, cognitive fatigue, and academic burnout — risks that are most pronounced among students with low AI literacy, high pre-existing psychological vulnerability, and patterns of AI use motivated by the desire to substitute for rather than supplement human social connection.

Self-Determination Theory and the technostress framework together provide a coherent explanatory architecture for these dual pathways: AI interaction promotes wellbeing when it satisfies students' needs for autonomy, competence, and relatedness, and undermines it when it frustrates those needs or supplants the human relationships through which they are most authentically met. AI literacy emerged as the most consistent individual-level protective moderator across the evidence base, underscoring the urgency of embedding AI competence education — encompassing not only technical but also psychological and ethical dimensions — within higher education curricula.

Three broader conclusions follow from this synthesis. First, the clinical potential of AI mental health tools in higher education is real, but it is realised only when tools are embedded within a human-centred service model that retains clear escalation pathways to professional care and active safeguards against emotional dependency. Second, the risks associated with unregulated AI use by psychologically vulnerable students are sufficiently documented to warrant urgent institutional policy action, including mandatory algorithmic bias auditing, robust data governance, and transparent consent mechanisms for all student-facing AI wellbeing tools. Third, the current evidence base — dominated by cross-sectional designs, geographically concentrated in China and the United States, and methodologically heterogeneous in its operationalisation of psychological wellbeing — is insufficient to support definitive causal conclusions. Longitudinal research employing standardised, AI-validated outcome measures across diverse cultural contexts represents the most pressing methodological priority for the field.

As AI technologies continue to evolve at a pace that consistently outstrips the research and regulatory infrastructures designed to govern them, the challenge for higher education is not whether to integrate AI into student wellbeing services, but how to do so in ways that are evidence-informed, ethically grounded, and genuinely human-centred. The present review offers a synthesised foundation for that endeavour.

REFERENCES

Abdallah, N., Al-Khalidi, M., & Hamdan, M. (2025). Systematic review of ChatGPT in higher education: Navigating impact on learning, wellbeing, and collaboration. Social Sciences & Humanities Open, 12, Article 101866. https://doi.org/10.1016/j.ssaho.2025.101866

Acosta-Enriquez, B. G., Saavedra-Lopez, M. A., Calle-Ramirez, X. M., Rojas-Montoya, M. M., & Hernandez-Vasquez, R. M. (2025). The mediating role of academic stress, critical thinking and performance expectations in the influence of academic self-efficacy on AI dependence:

Case study in college students. Computers in Human Behavior Reports, 17, Article 100608. https://doi.org/10.1016/j.chbr.2025.100608

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. AI and Ethics, 2(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

Auerbach, R. P., Mortier, P., Bruffaerts, R., Alonso, J., Benjet, C., Cuijpers, P., Demyttenaere, K., Ebert, D. D., Green, J. G., Hasking, P., Murray, E., Nock, M. K., Pinder-Amaker, S., Sampson, N. A., Stein, D. J., Vilagut, G., Zaslavsky, A. M., Kessler, R. C., & WHO WMH-ICS Collaborators. (2018). WHO World Mental Health Surveys International College Student Project: Prevalence and distribution of mental disorders. Journal of Abnormal Psychology, 127(7), 623–638. https://doi.org/10.1037/abn0000362

Campbell Academic Technology Services. (2025). AI in higher education: A meta summary of recent surveys of students and faculty. Campbell University. https://sites.campbell.edu/academictechnology/2025/03/06/ai-in-higher-education-a-summary-of-recent-surveys-of-students-and-faculty/

Chen, C., Lam, K. T., Yip, K. M., So, H. K., Lum, T. Y. S., Wong, I. C. K., Yam, J. C., & Chui, C. S. L. (2025). Comparison of an AI chatbot with a nurse hotline in reducing anxiety and depression levels in the general population: Pilot randomized controlled trial. JMIR Human Factors, 12, Article e65785. https://doi.org/10.2196/65785

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

De Freitas, J., Uğuralp, A. K., Uğuralp, Z. O., & Puntoni, S. (2024). AI companions reduce loneliness (Working Paper No. 24-078). Harvard Business School. https://www.hbs.edu/ris/Publication%20Files/24-078_a3d2e2c7-eca1-4767-8543-122e818bf2e5.pdf

Duong, C. D., Nguyen, T. H., & Ngo, T. V. H. (2025). Harnessing self-control and AI: Understanding ChatGPT's impact on academic wellbeing. Computers in Human Behavior, 164, Article 108512. https://doi.org/10.1016/j.chb.2024.108512

Feng, Y., Hang, Y., Wu, W., Song, X., Xiao, X., Dong, F., & Qiao, Z. (2025). Effectiveness of AI-driven conversational agents in improving mental health among young people: Systematic review and meta-analysis. Journal of Medical Internet Research, 27, Article e69639. https://doi.org/10.2196/69639

Freeman, J. (2025). Student generative AI survey 2025. Higher Education Policy Institute. https://www.hepi.ac.uk/reports/student-generative-ai-survey-2025/

Frontiers in Education. (2025). Ethical and regulatory challenges of generative AI in education: A systematic review. Frontiers in Education, 10, Article 1565938. https://doi.org/10.3389/feduc.2025.1565938

Gong, B., Luo, H., Zhang, S., Liu, Y., & Liang, D. (2026). Exploring the formation of learning burnout among college students in AI context: A serial mediation mechanism of AI dependence and addiction based on the I-PACE model. Frontiers in Computer Science, 7, Article 1756441. https://doi.org/10.3389/fcomp.2026.1756441

He, Y., Yang, L., Qian, C., Li, T., Su, Z., Zhang, Q., & Hou, X. (2023). Conversational agent interventions for mental health problems: Systematic review and meta-analysis of randomized controlled trials. Journal of Medical Internet Research, 25(1), Article e43862. https://doi.org/10.2196/43862

Hong, Q. N., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M. P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M. C., Vedel, I., & Pluye, P. (2018). The

Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. Education for Information, 34(4), 285–291. https://doi.org/10.3233/EFI-180221
Jiang, Y., Liang, X., & Zhao, H. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. Frontiers in Psychology, 16, Article 1498132. https://doi.org/10.3389/fpsyg.2025.1498132
Klimova, B., & Pikhart, M. (2025). Psychological risks of overdependence on AI in higher education: Technostress, digital fatigue, and social isolation. Education and Information Technologies, 30, 8541–8558. https://doi.org/10.1007/s10639-024-13200-x
Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2025). Artificial intelligence in higher education: The impact of need satisfaction on artificial intelligence literacy mediated by self-regulated learning strategies. Behavioral Sciences, 15(2), Article 165. https://doi.org/10.3390/bs15020165
Laestadius, L., Bishop, A., Gonzalez, M., Illenčík, D., & Campos-Castillo, C. (2024). Too human and not human enough: A grounded theory analysis of mental health harms from emotional dependence on the social chatbot Replika. New Media & Society, 26(10), 5923–5941. https://doi.org/10.1177/14614448221142007
Li, H., Zhang, R., Lee, Y. C., Kraut, R. E., & Mohr, D. C. (2023). Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. npj Digital Medicine, 6(1), Article 236. https://doi.org/10.1038/s41746-023-00979-5
Liu, H., Peng, H., Song, X., Xu, C., & Zhang, M. (2022). Using AI chatbots to provide self-help depression interventions for university students: A randomized trial of effectiveness. Internet Interventions, 27, Article 100495. https://doi.org/10.1016/j.invent.2022.100495
Liu, Z., & Xie, M. (2025). Research on data-driven strategy of integration of mental health education and ideological and political education in colleges and universities. International Journal of Healthcare Information Systems and Informatics, 20(1), 1–24. https://doi.org/10.4018/IJHISI.374199
Maples, B., Cerit, M., Vishwanath, A., & Pea, R. (2024). Loneliness and suicide mitigation for students using GPT3-enabled chatbots. npj Mental Health Research, 3(1), Article 4. https://doi.org/10.1038/s44184-023-00047-6
Mason, A., Rapsey, C., Sampson, N., Lee, S., Alonso, J., Altwaijri, Y., Andersson, C., Atwoli, L., Auerbach, R. P., Bantjes, J., Baumeister, H., Bendtsen, M., Benjet, C., & WMH-ICS Collaborators. (2025). Prevalence, age-of-onset, and course of mental disorders among 72,288 first-year university students from 18 countries in the World Mental Health International College Student (WMH-ICS) initiative. Journal of Affective Disorders, 370, 214–225. https://doi.org/10.1016/j.jad.2025.01.078
McKenzie, J. E., Brennan, S. E., Ryan, R. E., Thomson, H. J., Johnston, R. V., & Thomas, J. (2023). Chapter 9: Summarizing study characteristics and preparing for synthesis. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), Cochrane handbook for systematic reviews of interventions (Version 6.4). Cochrane. https://training.cochrane.org/handbook
Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, Article n71. https://doi.org/10.1136/bmj.n71
Popay, J., Roberts, H., Sowden, A., Petticrew, M., Arai, L., Rodgers, M., Britten, N., Roen, K., & Duffy, S. (2006). Guidance on the conduct of narrative synthesis in systematic reviews: A

product from the ESRC methods programme. Lancaster University. https://doi.org/10.13140/2.1.1018.4643

Rackoff, G. N., Zhang, Z. Z., & Newman, M. G. (2025). Chatbot-delivered mental health support: Attitudes and utilization in a sample of U.S. college students. Digital Health, 11, Article 20552076241313401. https://doi.org/10.1177/20552076241313401

Rossettini, G., Palese, A., & Corbella, M. (2025). Effectiveness of artificial intelligence chatbots on mental health and well-being in college students: A rapid systematic review. Frontiers in Psychiatry, 16, Article 1621768. https://doi.org/10.3389/fpsyt.2025.1621768

Shimizu, A., Takashina, M., Okubo, R., Noguchi-Watanabe, M., & Narita, Z. (2026). AI companions and subjective well-being: Moderation by social connectedness and loneliness. Technology in Society, 81, Article 102742. https://doi.org/10.1016/j.techsoc.2026.102742

Song, D., Oh, E. Y., & Rice, M. (2025). Linking digital competence, self-efficacy, and digital stress to perceived interactivity in AI-supported learning contexts. Scientific Reports, 15, Article 32145. https://doi.org/10.1038/s41598-025-18873-3

Song, X., Lv, H., Wei, C., & Jiang, R. (2025). AI-assisted psychological intervention mechanisms for university students in the context of new media technologies. Frontiers in Psychology, 16, Article 1619818. https://doi.org/10.3389/fpsyg.2025.1619818

Stănescu, D. F., & Romașcanu, M. (2025). Mental health in the "era" of artificial intelligence: Technostress and the perceived impact on anxiety and depressive disorders — an SEM analysis. Frontiers in Psychology, 16, Article 1600013. https://doi.org/10.3389/fpsyg.2025.1600013

Sun, J., Chen, X., & Li, W. (2025). Use of AI-based mental health tools and psychological well-being among Chinese university students: A parallel mediation model of emotional self-efficacy and perceived autonomy. Scientific Reports, 15, Article 24013. https://doi.org/10.1038/s41598-025-24013-8

Tan, S. C., Lim, C. P., & Wong, A. (2025). The mediating effects of needs satisfaction on the relationship between teacher support and student engagement with generative AI chatbots from a self-determination theory perspective. Education and Information Technologies, 30, 11203–11228. https://doi.org/10.1007/s10639-025-13574-w

Tang, X., Zeng, Z., Huang, H., & Symonds, J. (2025). Quality appraisal tools for quantitative, qualitative, and mixed-methods studies: A review and a brief new checklist. ECNU Review of Education, 8(2), 1–28. https://doi.org/10.1177/20965311251371227

Wang, Y., Li, X., Zhang, Q., Yeung, D., & Wu, Y. (2025). Effect of a cognitive behavioural therapy–based AI chatbot on depression and loneliness in Chinese university students: Randomized controlled trial with financial stress moderation. JMIR mHealth and uHealth, 13, Article e63806. https://doi.org/10.2196/63806

Wu, Q., Zhang, L., & Chen, H. (2024). AI technology panic — Is AI dependence bad for mental health? A cross-lagged panel model and the mediating roles of motivations for AI use among adolescents. Patient Preference and Adherence, 18, 631–643. https://doi.org/10.2147/PPA.S449255

Xia, Q., Chiu, T. K. F., Lee, M., Sanusi, I. T., Dai, Y., & Chai, C. S. (2025). Artificial intelligence in higher education: The impact of need satisfaction on artificial intelligence literacy mediated by self-regulated learning strategies. Behavioral Sciences, 15(2), Article 165. https://doi.org/10.3390/bs15020165

Xu, L., Zhang, Y., & Liang, R. (2025). The role of AI in university students' mental health: A bibliometric review. Discover Social Science and Health, 5, Article 47. https://doi.org/10.1007/s44155-025-00300-7

Yan, J., Wu, C., Tan, X., & Dai, M. (2025). The influence of AI-driven personalized foreign language learning on college students' mental health: A dynamic interaction among pleasure, anxiety, and self-efficacy. Frontiers in Public Health, 13, Article 1642608. https://doi.org/10.3389/fpubh.2025.1642608
Yang, Z., & Dai, X. (2025). How generative artificial intelligence transforms teaching and influences student wellbeing in future education. Frontiers in Education, 10, Article 1594572. https://doi.org/10.3389/feduc.2025.1594572
Zhai, S., Zhang, S., Rong, Y., & Rong, G. (2025). Technology-driven support: Exploring the impact of artificial intelligence on mental health in higher education. Education and Information Technologies, 30, 13931–13959. https://doi.org/10.1007/s10639-025-13352-8
Zhang, M., Chen, Y., & Liu, X. (2025). AI in college students' mental health education: Opportunities, challenges, and strategic responses. Frontiers in Psychology, 16, Article 1794568. https://doi.org/10.3389/fpsyg.2026.1794568
Zhang, X., Li, Q., & Wang, H. (2024). AI-driven personalized physical exercise and mindfulness intervention system: Optimization of academic performance and mental health in college students. Scientific Reports, 15, Article 37028. https://doi.org/10.1038/s41598-026-37028-6
Zwaan, J., Rosmalen, J., & Oldehinkel, A. J. (2023). Prevalence of mental disorders among Norwegian college and university students. eClinicalMedicine, 65, Article 102252. https://doi.org/10.1016/j.eclinm.2023.102252