Journal of Society Counseling
Vol. 4 No. 3, December 2026

Psychological Outcomes and Academic Resilience in University Students' Generative AI Use. A Critical Review of Retrieved Evidence

Muhamad Faqih Irsyad[1, 4], Cristin Mutiara Damanik[2], Widya Ayu Marliana[2], Waliyadin[3]
[1] *Universitas Islam Negeri Walisongo Semarang, Indonesia*
[2] *Universitas Negeri Semarang, Indonesia*
[3] *University of Canberra, Australia*
[4] *Flinders University, Australia*

Corresponding Author: irsyad_mf@walisongo.ac.id

ARTICLE INFO
Article history:
Received
September 23, 2026
Revised
Oktober 01, 2026
Accepted
Oktober 12, 2026

ABSTRACT

Generative artificial intelligence (GenAI) is associated with diverse psychological experiences in university learning, but routine use and designed interventions require different interpretations. This critical review examines psychological outcomes, correlates, and direct resilience-related evidence in reports identified through searches of Scopus, ERIC, and the SpringerLink publisher platform on 18 September 2026. The recorded search yielded 1,013 records; 50 duplicates were removed, 963 records were screened, and 45 candidate reports were sought. A revision-stage retrieval audit increased assessed reports from 12 to 44. One report remained unavailable, and one was excluded because GenAI-specific exposure could not be separated from broader AI use. The synthesis therefore includes 43 reports: 37 observational or task-context reports, four educational intervention reports, and two psychological-support trials. Dependence, anxiety, efficacy beliefs, literacy, and regulation showed heterogeneous associations; neither frequent use nor anxiety uniformly indicated harm. A classroom comparison measured academic resilience, a survey measured academic buoyancy, and a single-group study examined buoyancy qualitatively. These findings correct the earlier inference that direct resilience-related evidence was absent. Intervention benefits were specific to programs, outcomes, and assessment periods. Non-probability sampling, self-report, confounding, heterogeneous measures, incomplete retrieval, and limitations in the original screening documentation preclude a comprehensive causal account. The authors propose counseling and teaching applications for evaluation rather than presenting established prevention or treatment effects.

Keywords: *Generative Artificial Intelligence; University Students; Academic Resilience; Academic Buoyancy; Self-Regulated Learning; Counseling; Critical Review.*

How to cite: Irsyad, M. F., Damanik, C. M., Marlina, W. A., & Waliyadin, W. (2026). Psychological Outcomes and Academic Resilience in University Students' Generative AI Use. A Critical Review of Retrieved Evidence. *Journal of Society Counseling*. 4(3). DOI: https://doi.org/10.59388/josc.v4i3.1079
Journal Homepage: https://journal.scidacplus.com/index.php/josc
This is an open-access article under the CC BY-SA license
https://creativecommons.org/licenses/by-sa/4.0/
Published by: ScidacPlus

INTRODUCTION

GenAI can provide explanations, writing feedback, code suggestions, and conversational support, but the psychological meaning of using these tools varies across activities. A student who requests feedback on an independently prepared draft, a student who delegates a difficult assignment, and a student participating in a self-compassion program encounter different demands and supports. Consequently, classifying GenAI as simply beneficial or harmful obscures differences in exposure, measurement, and research design.

This review uses psychological adaptation as an organizing domain rather than a shared outcome. It covers regulation, affective experience, perceived competence, engagement, and well-being explicitly connected to GenAI activity. Self-regulated learning (SRL) concerns planning, monitoring, strategy use, and reflection (Pintrich, 2004; Zimmerman, 2002). Self-efficacy concerns beliefs about capability in a specified activity (Bandura, 1977). These constructs may function as outcomes, correlates, statistical mediators, or moderators. Their roles must be read from each study rather than assigned uniformly by the review.

Academic resilience and academic buoyancy require narrower treatment. Resilience concerns adaptive responses to substantial academic difficulty or adversity, whereas buoyancy concerns ordinary setbacks and pressures (Martin & Marsh, 2008). A dedicated instrument such as the Academic Resilience Scale provides one operational approach (Cassidy, 2016); other explicit measures require their own validity assessment. Qualitative accounts of responding to setbacks can inform understanding but are not equivalent to measured scale change. Higher engagement, better well-being, or stronger SRL alone cannot establish resilience.

Related theoretical perspectives also require restraint. Self-determination theory distinguishes autonomy, competence, and relatedness as motivational needs (Ryan & Deci, 2020). Self-compassion describes responding supportively to oneself in difficulty (Neff, 2003). Both inform questions about learning and support, but neither makes an empirical finding in a GenAI context true by definition. The possibility that assistance can coexist with dependence is treated here as a hypothesis about learning arrangements, not a validated psychological threshold.

Recent reviews already address psychological and regulatory aspects of educational AI. Abdallah et al. (2025) synthesize ChatGPT-related learning, well-being, and collaboration; Lan and Zhou (2025) examine AI-supported SRL more broadly. Xia, Liu, et al. (2026) address GenAI designs for SRL, while An et al. (2026) focus on overreliance. The present review therefore offers a counseling-oriented distinction among measured constructs, observational associations, and outcomes of specified interventions. It does not claim to be the first psychological review or a comprehensive census of the literature.

Three questions guide the synthesis: (1) What psychological constructs, including resilience and buoyancy, are directly assessed? (2) What associations are reported in observational and task-context research, and what outcomes are reported in educational or psychological-support interventions? (3) Which counseling and teaching implications are plausible, and which causal or transfer claims remain untested?

METHODS

Review Scope and Reporting

The article reports a critical review of retrieved evidence arising from a documented search and a revision-stage audit. PRISMA 2020 terminology makes the selection flow visible (Page et al., 2021), without implying that every recommended systematic-review procedure was completed. The review was not prospectively registered, and no formal dated protocol was

established before screening. The authors discussed the scope, thematic focus, and content collaboratively. The search strategy and recorded eligibility criteria are provided in Supplement S1. Revision-stage clarifications and retrieval changes are identified explicitly.

Search Sources and Eligibility

The search log records searches on 18 September 2026 in Scopus (231 records), ERIC (108), and SpringerLink (674). SpringerLink is a publisher platform, not a multidisciplinary indexing database. The logged period was 2022–2026. Three concept blocks combined GenAI terms, psychological constructs, and university-student terms; risk and protective-factor terms were not mandatory. Scopus used TITLE-ABS-KEY. Supplement S1 reproduces the logged strings, counts, and limits. The authors confirm that screening retained English-language empirical journal articles and excluded conference proceedings, considering psychology, social sciences, education/educational psychology and related fields relevant to the review. These are screening criteria; conditionally worded limits in the search log do not establish which interface filters were executed.

The review questions are organized using population–exposure–outcome (PEO): university/college students (population), GenAI use or a specified GenAI intervention (exposure), and explicitly assessed psychological constructs (outcomes). Eligible designs include qualitative, quantitative, and mixed-methods primary research. This mapping clarifies the revision's scope; it does not imply a prospectively registered framework.

Eligibility required university or college students; GenAI as the central exposure, task resource, or intervention; an explicitly analyzed psychological construct; and primary empirical data. We included qualitative, quantitative, and mixed-methods reports. Pure performance studies without a psychological construct, nonstudent populations, secondary research, and undifferentiated general-AI exposure were outside scope. Educational packages and psychological-support programs were retained as separate streams. This revision-stage clarification is reported as such; it is not represented as a prospectively registered rule.

PsycINFO, APA PsycArticles, and Web of Science were not included in the documented search, and a systematic grey-literature or citation-chaining search is not documented. The revision used targeted DOI and publisher checks to retrieve and identify existing shortlisted reports, not a new comprehensive database search. These checks also informed contextual comparisons with recent reviews; those reviews were not added as primary studies.

Screening and Retrieval Audit

The workbook contains 1,013 bibliographic records, 50 duplicate flags, and 963 unique records. First-pass screening was conducted by Muhamad Faqih Irsyad. Second-pass screening was conducted collaboratively by authors 2, 3, and 4 (Cristin Mutiara Damanik, Widya Ayu Marliana, and Waliyadin) through discussion. Uncertain inclusion or exclusion decisions were discussed by the authors until agreement was reached. Microsoft Excel organized the records and screening decisions. ChatGPT assisted with information mapping, organization, and processing against the recorded criteria; the authors remained responsible for substantive eligibility decisions. Independent duplicate screening was not performed, and separate reviewer agreement scores are not reported.

The second-pass criteria required higher-education students, GenAI as the central exposure/context, a relevant psychological construct, primary empirical research, and a direct analytic link between GenAI and the psychological construct. The workbook records an initial

Include/Maybe pool of 195, a final shortlist of 45 and nine reinstated records. The authors clarify that no numerical cap was imposed: the final number resulted from sequential application of eligibility criteria, and eligible reports were not excluded solely to keep the shortlist below 50. A below-50 statement in the historical workbook summary is therefore not reported as an applied exclusion rule. A complete decision-by-decision reconstruction of the historical second pass remains unavailable. The recorded title/abstract exclusion count is 918.

The revision reconciled all 45 shortlisted entries against the 686-page PDF compilation and targeted publisher full texts. Forty distinct shortlisted reports were located in the compilation; repeat copies of the self-compassion and digital-stress trials were not counted twice. Four further reports were retrieved from publisher or PubMed Central full texts: Sayed et al. (2024), Kong et al. (2026), Besalti (2025), and Arab (2026). One title/DOI mismatch was corrected: SC230 concerns Kong et al.'s problematic-use study, not a duplicate of the self-compassion trial. Retrieval was audited on 30 September–1 October 2026.

Original full texts were collected by M. Faqih Irsyad through Scopus and ERIC links, ScienceDirect, publisher pages, and other available full-text sources. ScienceDirect served as a retrieval source; it is not added to the logged database identification counts. Access restrictions prevented retrieval of some reports. The authors cannot reconstruct the precise historical reason why the initial assessment covered only 12 reports. These reports are not described as a representative, purposive, or otherwise procedurally selected sample. The revision audit, rather than an inferred historical explanation, supplies the current reconciliation trail.

Forty-four reports were assessed. Wu et al. (2026; DOI 10.1016/j.actpsy.2026.106874) was excluded from the core synthesis because recruitment covered tutoring systems, chat agents, and adaptive platforms without separable GenAI-specific exposure results. Rehman et al. (2026; DOI 10.1002/jcal.70312) remained unassessed because full-text access was unsuccessful; its abstract was not substituted for full-text appraisal. Thus, 43 reports were included, one excluded at full text, and one not retrieved (2.2% of the 45 sought). Supplement S2 identifies every shortlisted report, its current decision, and the audit trail.

Data Extraction and Narrative Methodological Critique

The revision extracted report identity, sample and setting, student/task context, exposure stream, psychological measures, analytic roles, finding direction, selected numerical results, and design limitations. The revision prioritized primary methods and results over the earlier summary. For example, Zhou and Wang's (2026) analytic sample was corrected from 613 to 500; the self-compassion trial distinguishes 225 enrolled from 220 analyzed participants. We kept component samples and pilot samples separate. No overall participant total is reported because some reports have multiple samples and overlap between reports cannot be ruled out.

Original data extraction was conducted by M. Faqih Irsyad. The authors collaboratively checked, reviewed, and discussed extracted information for relevance to the research aims. This was a collaborative review, not independent duplicate extraction. The revision-stage reconciliation and expanded extraction were assisted by ChatGPT; no independent duplicate verification of the revised extraction is claimed.

No formal structured quality appraisal was conducted. We examined methodological limitations narratively and used them to qualify the conclusions. This critique considers recruitment, exposure and construct measurement, temporal ordering, confounding, comparators, allocation and clustering, missingness, outcome assessment and follow-up as relevant to each report. For qualitative and Q-methodological evidence, interpretation is restricted to the

participants, reported accounts and analytic context. Supplement S3 records report-specific methodological constraints and source locations; S4 links those constraints to the findings. No MMAT ratings, numerical quality scores, or formal certainty grades are reported.

Synthesis Approach

A structured narrative synthesis grouped reports first by exposure and design, then by the construct actually assessed. Deductive groups covered affect/distress, regulation/efficacy, dependence, and direct resilience/buoyancy; reading the findings added contextual distinctions such as authorship, psychological ownership, and institutional guidance. A report could contribute to more than one construct group, but this did not create independent evidence units. Qualitative findings were retained as reported experiences or interpretations. Statistical mediation and moderation were not translated into temporal mechanisms.

For interventions, the synthesis emphasizes comparators, assessment periods, and between-group or group-by-time results, following relevant reporting principles from SWiM (Campbell et al., 2020). SWiM was not used as a substitute for qualitative thematic methods. A pooled estimate was not calculated because outcomes, exposures, and study designs did not define a common estimand. The review does not vote-count significance or rank constructs by the number of positive findings. Reported methodological limitations determine how narrowly each result is interpreted.

RESULTS AND DISCUSSION

Evidence base after retrieval reconciliation

Figure 1 presents the reconciled flow. The 43 included reports comprise 37 observational or task-context reports, four educational intervention reports, and two psychological-support trials. The first stream includes 23 quantitative cross-sectional reports, three time-lagged quantitative surveys, eight observational mixed-methods reports (one time-lagged), two qualitative studies, and one Q-methodological study. Educational studies comprise one two-class comparison, one single-group mixed-methods study, one individually randomized trial, and one mixed-methods feedback comparison with inconsistent design terminology. Two further randomized trials tested psychological support. These are report-level classifications, not counts of statistically independent samples.

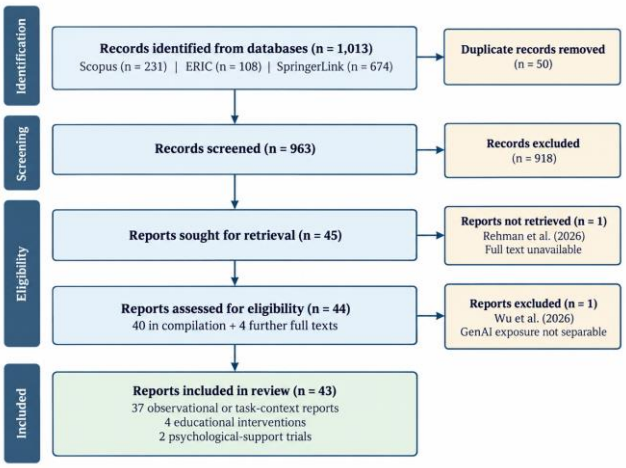


Figure 1. Reconciled selection flow. Historical identification and screening counts come from the workbook; retrieval and eligibility reflect the revision-stage audit. "Reports included" avoids implying that multicomponent reports contain only one independent study.

The evidence now includes 2024 reports, notably S. Zhang et al. and Sayed et al.; the original concentration in 2025–2026 reflected incomplete assessment, not demonstrated absence of earlier eligible work. No 2022–2023 publication appears in the included set, but the search and screening limitations prevent interpreting this as a field-wide absence. Publication dates also differ from data-collection dates: for example, X. Yang et al. (2026) collected data in 2023. The set remains concentrated in China while also including Türkiye, Saudi Arabia, Spain, Japan, South Korea, the United States, the United Kingdom, France, Israel, Iran, Ethiopia, and Singapore. Where the study setting was not clearly established, it was not inferred from an author's affiliation.

Supplement S4 provides every included report's sample, context, findings, and narrative methodological constraints. Table 1 summarizes the exposure streams. Abbreviations used below are structural equation modeling (SEM), partial least squares SEM (PLS-SEM), English as a foreign language (EFL), and English-medium instruction (EMI).

Table 1. Exposure streams and limits of inference. Full report-level details appear in Supplement S4.

Evidence stream	Reports	What the evidence can support
Observational or task-context research	37	Associations and accounts of learning experiences. Includes cross-sectional, time-lagged, qualitative, Q, and mixed-methods reports; does not establish effects of changing ordinary GenAI use.
Educational interventions	4	Outcomes of specific feedback or instructional arrangements. GenAI is often one component of a larger package; single-group findings do not identify an intervention effect.
Psychological-support trials	2	Short-term outcomes of assigned self-compassion or function-specific support packages; does not establish resilience gains, routine-use risk factors, or equivalence to counseling.

Dependence and psychological strain

Dependence-related reports repeatedly modeled links with stress, motivation, efficacy beliefs, and perceived usefulness, but the direction of influence remains uncertain. Cross-sectional studies linked academic stress with dependence, burnout, or anxiety (X. Liu et al., 2026; Wang et al., 2026; Gu et al., 2026). Fu (2026) added perceived competitive academic conditions. Time-lagged reports improved measurement separation: C. Zhang (2026) examined efficacy, stress, and usefulness, while Kong et al. (2026) examined affect and avoidance-oriented motivation. However, time separation alone did not establish all steps of the proposed serial pathways or exclude reciprocal effects.

The evidence does not support identifying frequency as a universal marker of problematic use. X. Yang et al. (2026) separated frequent from excessive chatbot use, while Arab (2026) reported different directions for comfort in discussing mental health and disruptive reliance. Besalti (2025) found an inverse relationship between use and academic well-being, mediated by self-control, in a separate cross-sectional sample, not a repeated-measures cohort. These findings concern different exposure definitions; combining them into a single dose–harm relationship would be misleading.

Perceived cognitive costs also require careful labeling. S. Zhang et al. (2024) and Huang and Wu (2025) reported students' accounts of reduced independent thinking, creativity, or reflection. These accounts matter for understanding difficulties but do not demonstrate measured deterioration in cognitive ability. Similarly, Meishar-Tal and Amzalag (2026) compared perceived capability with and without ChatGPT, rather than experimentally measuring competence loss after tool removal.

Anxiety is not a single construct or a uniformly harmful correlate

AI anxiety, writing anxiety, academic anxiety, technostress, and general digital stress were kept distinct. Zhou and Wang (2026) studied writing anxiety in relation to feedback literacy. Gündüz et al. (2026) examined AI anxiety as a moderator of ChatGPT-use–enjoyment associations; their factor-level analysis distinguished broader societal concerns from apprehension related to interactions. Mohamed et al. (2026) examined AI anxiety in a purposively selected gifted EFL population, limiting generalization beyond that group. In that cross-sectional model, AI anxiety statistically mediated the gifted-behavior–motivation association; this does not establish a temporal mechanism.

Contrasting findings qualify the earlier risk inventory. E. Kim (2026) found that anxiety was positively associated with verification and revision in a writing context. Dizon et al. (2025) found neither high average technostress nor a significant proficiency-group difference, while qualitative responses still described accuracy concerns. Karal and Özdemir Sarialioglu (2025) observed negative associations between anxiety and regulation/acceptance in a small course-based sample. Thus, the meaning of anxiety depends on what is measured and which behavior is examined. Evidence that concern accompanies checking does not show that increasing anxiety improves learning.

Literacy and regulation show conditional associations

The enlarged evidence base provides more than the original single study on AI literacy, but it still does not establish literacy as a universal protective intervention. Shi et al. (2025) associated literacy with writing performance and GenAI-related well-being; the SRL–well-being relationship was small and indirect. Xiaohui and Khan (2026) modeled literacy as a moderator of dependence-related helplessness, and Gao et al. (2026) linked literacy and critical evaluation with effective use across time-lagged surveys. Cengiz and Peker (2025) examined literacy in an anxiety model. These measure different constructs and play different roles; they do not estimate the effect of a common literacy curriculum.

Regulation also showed nonuniform patterns. Galindo-Domínguez, Delgado, et al. (2026) found a positive goal-setting–overreliance association, along with negative indirect associations through perseverance and learning from mistakes. Galindo-Domínguez, Sainz-de-la-Maza, et al. (2026) linked procrastination to motivation and dependence. Y. Liu and Y. Liu (2026) modeled regulation and procrastination between usefulness and dependence. By contrast, Xue and Chen (2026) treated writing SRL as an outcome related to efficacy and feedback engagement. SRL cannot therefore be relabeled as the same protective mechanism in all reports.

Other learner resources were similarly context-dependent. X. Chen et al. (2026) reported self-control, meaning, and engagement associations conditional on dependence. Xia, Jiang, et al. (2026) found personality associations across SRL phases but limited needs-satisfaction moderation; neither conditional extraversion slope was significant. Consequently, needs satisfaction is not listed as an established protective factor. Adekoya et al. (2026) provided

complementary qualitative accounts of autonomy, competence, and relatedness among international postgraduates, which inform interpretation without validating the survey interactions.

Direct and indirect resilience-related evidence

The retrieval audit changes the original central conclusion. W. Zheng et al. (2026) explicitly measured academic resilience with a 16-item scale; S. J. Kim et al. (2026) measured academic buoyancy with four items concerning routine setbacks. Sayed et al. (2024) examined buoyancy through narrative accounts. Kanwal (2025) included coping and resilience-related perceptions within a broader writing questionnaire. Table 2 separates these evidence types from proximal constructs. Claims of no direct resilience-related research are no longer retained.

Table 2. Resilience-related measurement distinctions. No common resilience effect size is inferred across these reports.

Report and assessment	Finding	Interpretation
W. Zheng et al. (2026) 16-item resilience scale; two classes, n = 83	Posttest favors instructional package; F = 6.042, p = .016, partial eta squared = .069.	Direct named resilience measure, but one class per condition and bundled pedagogy prevent attributing the result to GenAI alone.
S. J. Kim et al. (2026) Four-item academic buoyancy scale; n = 273	Responsible ChatGPT use associated with buoyancy, grit and well-being.	Direct buoyancy measurement; cross-sectional mediation does not establish recovery or causal improvement.
Sayed et al. (2024) Narratives; n = 28	Participants described persistence and adapting to speaking challenges.	Qualitative buoyancy evidence; no comparative psychological effect estimate.
Kanwal (2025) Broader writing-perceptions questionnaire; n = 142	Favorable coping and resilience-related perceptions.	Limited construct specificity; not interchangeable with a dedicated resilience scale.
Other psychological outcomes	SRL, efficacy, engagement, emotion regulation, distress, and well-being.	Psychologically relevant outcomes, but not automatic proxies for resilience or buoyancy.

Educational and psychological-support interventions

The four educational reports differed substantially. W. Zheng et al. (2026) combined lab rotation, GenAI, and peer review; the comparison cannot isolate the AI component. Zhu and Hashemifardnia (2026) randomized 60 students to a twelve-week instructional routine or traditional instruction. Baseline-adjusted analyses favored the package for intolerance of uncertainty and academic emotion regulation, but these were self-reported outcomes in one convenience sample. Sayed et al. (2024) supplied single-group speaking and narrative findings. None establishes a general effect of adopting GenAI across university settings.

Yilmaz et al. (2026) compared trace-informed GenAI feedback with tutor feedback among 46 students. Task-strategy posttest results favored GenAI ($p = .044$, $r = .35$), whereas time management did not meet the conventional significance threshold ($p = .057$); other reported SRL dimensions were not significantly different. The article states random allocation but also labels

the design quasi-experimental. That ambiguity is retained rather than silently resolved in favor of stronger evidence. Trace indicators are behavioral proxies for SRL dimensions, not complete assessments of the construct.

The psychological trials address a separate question. T. X. Chen et al. (2026) enrolled 225 students and analyzed 220, testing three self-compassion chatbot sessions against an active chatbot control. Group-by-time interactions favored the intervention for self-compassion (partial eta squared = .049) and self-criticism (.059), both $p < .001$. The post-intervention self-compassion difference was $d = .36$; the reported 95% confidence interval for the raw mean difference was [.06, .37]. Academic engagement showed a group-by-time interaction, but the simple posttest group comparison was not significant; burnout and procrastination interactions were also nonsignificant. These distinctions prevent presenting selective outcomes as broad improvement in academic functioning.

Q. Yang et al. (2026) randomized 99 students across emotional-support, problem-solving, and waitlist conditions for a fourteen-day intervention. Outcomes varied by digital-stress dimension: emotional support versus waitlist favored lower availability stress ($d = -1.29$), while problem-solving support favored lower online vigilance ($d = -1.30$), both $p < .001$. Both packages favored lower anxiety ($d = -.78$ and $-.59$, respectively). Although the depression group-by-time interaction was significant, neither post-intervention contrast against waitlist was significant. Digital stress was the treatment target, not evidence of harm caused by GenAI. The trial used intention-to-treat analysis and imputation but lacked objective usage logs. Both psychological trials were brief, and neither tested equivalence to professional counseling, crisis suitability, or durable academic resilience.

Evidence quality and sensitivity of conclusions

The narrative methodological critique identifies recurrent limits rather than a hierarchy of "high-quality" versus "low-quality" papers. Large samples improve precision for their models but do not correct non-probability recruitment, common measurement sources, or omitted confounding. Time-lagged studies provide partial temporal separation yet remain observational. Qualitative studies clarify meanings and contextual variation but do not estimate population prevalence. Experimental allocation strengthens specific comparisons, but bundled pedagogy, non-blinded outcomes, small samples, missingness, and limited follow-up restrict transfer.

The revised interpretation remains cautious when weaker evidence is set aside. Excluding broad-AI exposure removes Wu et al.'s cognitive-flexibility findings from the core GenAI account. Omitting single-group intervention evidence leaves no comparative buoyancy effect from Sayed et al. Omitting the two-class instructional comparison removes the direct resilience intervention finding, while the buoyancy survey remains associational. Removing cross-sectional mediation models leaves no validated multistage causal pathway. This qualitative sensitivity assessment shows which conclusions depend on particular designs; it is not a numerical robustness analysis.

Comparison with previous reviews

The mixed pattern of support and difficulty aligns with Abdallah et al.'s (2025) broad attention to learning, well-being, and collaboration. The present synthesis separates outcomes of designed support from correlates of routine use, so favorable chatbot-program findings cannot offset observational dependence associations as if they estimated the same effect. Lan and Zhou (2025) and Xia, Liu, et al. (2026) foreground AI-supported regulation and learning design; the

present findings further distinguish regulation as an outcome, correlate, or statistical intermediary. An et al.'s (2026) focus on overreliance provides a relevant comparison for dependence-related findings, but the anxiety and resilience-related reports here broaden the questions considered. Differences in scope, constructs, designs, and incomplete retrieval plausibly explain differences in emphasis; they do not demonstrate superiority or comprehensive coverage of this review.

Implications for counseling and teaching

The following applications are proposals for prospective evaluation. At a universal level, universities could teach students to set task goals, evaluate generated claims, explain accepted and rejected suggestions, and demonstrate an independent attempt. Literacy and regulation studies motivate these practices, but no included report establishes that this combined program prevents dependence better than ordinary instruction. Evaluation should examine independent transfer and functioning alongside satisfaction and immediate performance.

Targeted support could differentiate concerns rather than use a single "AI anxiety" label. A student worried about writing feedback may need a different discussion from one who cannot complete work without assistance or one who describes loss of authorship. Li et al. (2026) and C. Zheng and Wang (2026) inform questions about ownership, verification, and conflicted reliance; their accounts do not establish diagnostic thresholds. Collaborative goals may include checking claims, retaining a record of reasoning, and monitoring interference with study routines. Frequency alone should not determine referral.

For individual support, persistent distress or functional interference should be considered through existing professional assessment and referral procedures. Optional chatbot programs should have clear scope, consent and data-governance arrangements, and accessible human support. These are proposed implementation boundaries, not demonstrated treatment pathways from this review. No included trial supports replacing professional counseling or using these programs as a crisis service. A stepped service model would require its own evaluation, including adverse experiences, equity, adherence, and follow-up.

Institutional conditions also warrant attention. Li et al. (2026), Adekoya et al. (2026), and Pavone (2026) describe concerns about authorship, legitimacy, assessment, and engagement. Clear task-specific expectations and opportunities to discuss uncertainty are plausible responses. Their effectiveness in reducing anxiety, concealment, or dependence has not been established. The proposed distinction between assistance that preserves learner participation and substitution that displaces it is therefore a research hypothesis, not a discovered threshold or a validated causal model.

Limitations of the review

Retrieval improved from 12 to 44 assessed reports, but one potentially relevant report remains unassessed. Its title and abstract concern resilience, making its absence relevant to the scope of the conclusions. The recorded search covered two indexing databases and one publisher platform; exact interface settings are not fully reproducible, and no comprehensive grey-literature or citation search is documented. The authors confirm that no numerical cap determined eligibility, but the incomplete historical decision trail limits assessment of selection bias. Resolving retrieval does not establish comprehensive search coverage.

The review was not prospectively registered and had no formal dated protocol before screening. Screening and original extraction checking were collaborative, without independent duplicate assessment. The historical reason for assessing only 12 reports cannot be reconstructed

fully, and the detailed second-pass decision trail remains incomplete. AI-assisted revision-stage extraction is not presented as independently verified in duplicate. No formal structured quality appraisal or formal certainty-of-evidence assessment was conducted. These limitations may affect eligibility, extraction, and interpretation. The synthesis is framed as a critical review of retrieved evidence, not a definitive systematic account. Heterogeneous constructs and uncertain sample overlap preclude an aggregate participant total or pooled adaptation effect.

CONCLUSION

This critical review includes 43 reports from 45 candidates, after 44 full-text assessments, one exposure-based exclusion, and one unresolved retrieval. The enlarged evidence base includes direct academic-resilience and buoyancy measures, as well as qualitative, resilience-related accounts. It also shows heterogeneous associations involving dependence, anxiety, literacy, efficacy beliefs, and regulation. Specific educational and psychological-support interventions offer preliminary, outcome-specific findings; they do not demonstrate a general causal pathway from GenAI use to resilience. Counseling and teaching applications should preserve distinctions among constructs, exposure types, and evidence designs, and should be evaluated for independent learning, functioning, adverse experiences, and durability. More complete searching, transparent independent review procedures, and stronger longitudinal and experimental studies remain necessary.

REFERENCES

Abdallah, N., Katmah, R., Khalaf, K., & Jelinek, H. F. (2025). Systematic review of ChatGPT in higher education: Navigating impact on learning, wellbeing, and collaboration. *Social Sciences & Humanities Open, 12, 101866.* https://doi.org/10.1016/j.ssaho.2025.101866

* Adekoya, O. D., Ajonbadi, H. A., Mordi, C., Samuel, P., & Nguyen, H. (2026). 'A double-edged tool': A psychological needs perspective of generative AI and postgraduate international students' engagement in UK higher education. *British Educational Research Journal, 52, 3063–3092.* https://doi.org/10.1002/berj.70138

An, C., Lu, K., & Yang, J. (2026). The dependency trap: A systematic review of the contributing factors and consequences of student over-reliance on generative AI in higher education. *Humanities and Social Sciences Communications, 13, 1604.* https://doi.org/10.1057/s41599-026-08959-2

* Arab, A. H. (2026). Between coping resource and risk factor: ChatGPT and social media use in relation to anxiety, depression, and somatization. *Frontiers in Human Dynamics, 8, 1722990.* https://doi.org/10.3389/fhumd.2026.1722990

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84(2), 191–215.* https://doi.org/10.1037/0033-295X.84.2.191

* Besalti, M. (2025). Harnessing Self-Control and AI: Understanding ChatGPT's Impact on Academic Wellbeing. *Behavioral Sciences, 15(9), 1181.* https://doi.org/10.3390/bs15091181

Campbell, M., McKenzie, J. E., Sowden, A., Katikireddi, S. V., Brennan, S. E., Ellis, S., Hartmann-Boyce, J., Ryan, R., Shepperd, S., Thomas, J., Welch, V., & Thomson, H. (2020). Synthesis without meta-analysis (SWiM) in systematic reviews: Reporting guideline. *BMJ, 368, l6890.* https://doi.org/10.1136/bmj.l6890

Cassidy, S. (2016). The Academic Resilience Scale (ARS-30): A new multidimensional construct measure. *Frontiers in Psychology, 7, 1787.* https://doi.org/10.3389/fpsyg.2016.01787

* Cengiz, S., & Peker, A. (2025). Generative artificial intelligence acceptance and artificial intelligence anxiety among university students: the sequential mediating role of attitudes toward artificial intelligence and literacy. *Current Psychology, 44, 7991–8000.* https://doi.org/10.1007/s12144-025-07433-7

* Chen, T. X., Cheng, C.-Y., & Hartanto, A. (2026). Caring with AI: The efficacy of a customised ChatGPT-delivered self-compassion intervention on college students' well-being and academic functioning. *Computers in Human Behavior Reports, 23, 101267.* https://doi.org/10.1016/j.chbr.2026.101267

* Chen, X., Cui, M., Sun, P., Xu, X., Ma, K., & Yan, L. (2026). Unpacking the relationship between self-control and academic engagement: the mediating role of meaning in life and the moderating role of GenAI dependence. *BMC Psychology, 14, 168.* https://doi.org/10.1186/s40359-025-03862-y

* Chen, Y., Chen, G., & Chen, J. (2026). Generative AI–social media coordinated learning and university students' psychological well-being: dual pathways and the buffering role of perceived support. *Frontiers in Psychology, 17, 1788850.* https://doi.org/10.3389/fpsyg.2026.1788850

* Dizon, G., Gold, J., & Barnes, R. (2025). Technostress and English Language Learning in the Age of Generative AI. *The EUROCALL Review, 32(2), 88–101.* https://doi.org/10.4995/eurocall.2025.23851

* Fu, F. (2026). Academic involution atmosphere and AI dependence among university students: the mediating role of academic stress and the moderating role of individual academic involution behaviors. *Frontiers in Psychology, 17, 1857123.* https://doi.org/10.3389/fpsyg.2026.1857123

* Galindo-Domínguez, H., Delgado, N., Sainz-de-la-Maza, M., & Etxabe, J.-M. (2026). Self-regulation and overreliance on artificial intelligence: Unpacking a paradox through a mixed-methods study in higher education. *Computers in Human Behavior, 181, 108985.* https://doi.org/10.1016/j.chb.2026.108985

* Galindo-Domínguez, H., Sainz-de-la-Maza, M., Campo, L., & Losada-Iglesias, D. (2026). The influence of learning motivation and procrastination on ChatGPT dependence. *RIED Revista Iberoamericana de Educación a Distancia, 29(1), 217–240.* https://doi.org/10.5944/ried.45497

* Gao, L., Sun, Y., & Khan, S. U. (2026). From enhancement to over-reliance: a mixed-method study of generative AI and sustainable learning performance. *Frontiers in Psychology, 17, 1847369.* https://doi.org/10.3389/fpsyg.2026.1847369

* Gu, C., He, B., & Zhang, X. (2026). The relationship between college students' AI technology dependence and learning burnout: a chain mediation analysis of technology acceptance and AI self-efficacy. *Frontiers in Psychology, 17, 1843366.* https://doi.org/10.3389/fpsyg.2026.1843366

* Gündüz, G. F., Ünal, K., & Özışık, C. (2026). The Effect of ChatGPT Usage on Foreign Language Enjoyment: The Mediating Role of Learning Effort and the Moderating Effect of Artificial Intelligence Anxiety. *Language Teaching Research Quarterly, 54, 362–384.* https://doi.org/10.32038/ltrq.2026.54.15

* Huang, T., & Wu, C. (2025). The chain mediating effect of academic anxiety and performance expectations between academic self-efficacy and generative AI reliance. *Computers and Education Open, 9, 100275.* https://doi.org/10.1016/j.caeo.2025.100275

* Kanwal, A. (2025). Exploring the Impact of ChatGPT on Psychological Factors in Learning English Writing among Undergraduate Students. *World Journal of English Language, 15(3), 404–413.* https://doi.org/10.5430/wjel.v15n3p404

* Karal, Y., & Özdemir Sarialioglu, R. (2025). Examining the Relationship between Undergraduate Students' Acceptance, Anxiety and Online Self-Regulation of Generative Artificial Intelligence. *International Journal of Technology in Education, 8(2), 445–466.* https://doi.org/10.46328/ijte.1065

* Kim, E. (2026). From AI anxiety to strategic regulation: How university students transform generative AI into a strategic learning resource. *Computers and Education: Artificial Intelligence, 10, 100622.* https://doi.org/10.1016/j.caeai.2026.100622

* Kim, S. J., Cha, J., Huh, C., Lee, M. J., & Choi, H. (2026). Responsible Use of ChatGPT on Academic Buoyancy, Grit, and Wellbeing. *Journal of Hospitality & Tourism Education, 38(3), 246–262.* https://doi.org/10.1080/10963758.2026.2653604

* Kong, Y., Dong, T., Yang, Z., Fang, Y., & Chen, N. (2026). From cognitive need to problematic use: A chained mediation path moderated by academic stress and AI literacy. *Frontiers in Psychology, 17, 1767454.* https://doi.org/10.3389/fpsyg.2026.1767454

Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *npj Science of Learning, 10, 21.* https://doi.org/10.1038/s41539-025-00319-0

* Li, X., Xian, X., & Du, P. (2026). From AI dependence to reflective collaboration: psychological ownership, competency anxiety, and perceived support in AI-assisted learning. *Frontiers in Psychology, 17, 1903784.* https://doi.org/10.3389/fpsyg.2026.1903784

* Liu, X., Liu, Y., Dai, Y., & Fu, J. (2026). Academic stress and university students' dependency on generative artificial intelligence: a multiple mediation model using PLS-SEM. *BMC Psychology, 14, 216.* https://doi.org/10.1186/s40359-026-03986-9

* Liu, Y., & Liu, Y. (2026). Association between perceived usefulness of generative AI for learning and generative AI dependency among university students in Changde, China: a cross-sectional study of statistical indirect effects. *Frontiers in Psychology, 17, 1859317.* https://doi.org/10.3389/fpsyg.2026.1859317

Martin, A. J., & Marsh, H. W. (2008). Academic buoyancy: Towards an understanding of students' everyday academic resilience. *Journal of School Psychology, 46(1), 53–83.* https://doi.org/10.1016/j.jsp.2007.01.002

* Meishar-Tal, H., & Amzalag, M. (2026). Mind the gap: Perceived academic self-efficacy, creativity, and critical thinking with and without ChatGPT. *Thinking Skills and Creativity, 62, 102246.* https://doi.org/10.1016/j.tsc.2026.102246

* Mohamed, A. M., Emran, A. Q., Abdelrady, A. H., & Ali El Deen, A. A. M. M. (2026). Giftedness and academic motivation in GenAI contexts: the moderating and mediating role of gender and AI anxiety. *Frontiers in Education, 11, 1762707.* https://doi.org/10.3389/feduc.2026.1762707

Neff, K. D. (2003). Self-compassion: An alternative conceptualization of a healthy attitude toward oneself. *Self and Identity, 2(2), 85–101.* https://doi.org/10.1080/15298860309032

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, n71.* https://doi.org/10.1136/bmj.n71

* Pavone, G. (2026). Generative AI in the Learning Process: Threat or Tool? Understanding the Role of Self-Esteem and Academic Anxiety in Shaping Student Motivations. *Journal of Marketing Education, 48(2), 177–200.* https://doi.org/10.1177/02734753251346857

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review, 16, 385–407.* https://doi.org/10.1007/s10648-004-0006-x

Rehman, N., Huang, X., Zhang, Y., & Mahmood, A. (2026). The nexus of Gen-AI features in higher education: Reducing cognitive load, building resilience, and personalising learning. *Journal of Computer Assisted Learning, 42(5), e70312.* https://doi.org/10.1002/jcal.70312

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology, 61, 101860.* https://doi.org/10.1016/j.cedpsych.2020.101860

* Sayed, B. T., Bani Younes, Z. B., Alkhayyat, A., Adhamova, I., & Teferi, H. (2024). To Be with Artificial Intelligence in Oral Test or Not to Be: A Probe into the Traces of Success in Speaking Skill, Psychological Well-Being, Autonomy, and Academic Buoyancy. *Language Testing in Asia, 14, 49.* https://doi.org/10.1186/s40468-024-00321-0

* Shi, J., Liu, W., & Hu, K. (2025). Exploring How AI Literacy and Self-Regulated Learning Relate to Student Writing Performance and Well-Being in Generative AI-Supported Higher Education. *Behavioral Sciences, 15(5), 705.* https://doi.org/10.3390/bs15050705

* Wang, W., Wu, Y., Fang, J., Yang, C., & Wen, L. (2026). When cognitive offloading becomes dependence: how AI dependence mediates the pathway from academic stress to burnout and anxiety. *BMC Psychology, 14, 1125.* https://doi.org/10.1186/s40359-026-04911-w

Wu, H., Wang, Z., & Wen, X. (2026). Examining interactive AI-supported learning environments: The mediating role of AI metacognition and the moderating role of cognitive flexibility. *Acta Psychologica, 266, 106874.* https://doi.org/10.1016/j.actpsy.2026.106874

* Xia, Q., Jiang, R., Zhang, Z., & Chiu, T. K. F. (2026). How Are Self-Determination Theory Needs Satisfaction and Personality Traits Associated with Self-Regulated Learning Using Generative Artificial Intelligence?. *Measurement: Interdisciplinary Research and Perspectives.* https://doi.org/10.1080/15366367.2026.2717599

Xia, Q., Liu, Q., Tlili, A., & Chiu, T. K. F. (2026). A systematic literature review on designing self-regulated learning using generative artificial intelligence and its future research directions. *Computers & Education, 240, 105465.* https://doi.org/10.1016/j.compedu.2025.105465

* Xiaohui, C., & Khan, T. J. (2026). AI dependency and academic motivation in higher education: the mediating role of learned helplessness and the moderating role of AI literacy. *Frontiers in Psychology, 17, 1896371.* https://doi.org/10.3389/fpsyg.2026.1896371

* Xue, J., & Chen, M. (2026). Unravelling the relationship between self-efficacy and self-regulated strategies in GenAI-assisted writing of postgraduates: the mediating role of feedback engagement. *Frontiers in Psychology, 17, 1786221.* https://doi.org/10.3389/fpsyg.2026.1786221

* Yang, Q., Wu, H., Du, X., Sun, Q., & Ren, Z. (2026). Emotional support or problem-solving? A randomized controlled trial of function-specific AI Chatbots for digital stress in college students. *Applied Psychology: Health and Well-Being, 18(4), e70208.* https://doi.org/10.1111/aphw.70208

* Yang, X., Liu, Y., Zheng, Y., Wang, M., Hou, J., Wang, Y., Cheng, R., Feng, B., Li, Z., & Wang, X. (2026). Associations between frequent and excessive generative AI chatbot use and common mental health problems in college students: examining academic and social mechanisms. *International Journal of Adolescence and Youth, 31(1), 2703815.* https://doi.org/10.1080/02673843.2026.2703815

* Yilmaz, M., Temur, H. B., Emmungil, L., Çelik, E., Gauthier, A., & Cukurova, M. (2026). Supporting self-regulated learning through generative AI feedback in online higher education: the importance of student perceptions of the source of feedback. *International Journal of Educational Technology in Higher Education, 23, 16.* https://doi.org/10.1186/s41239-026-00592-y

* Yu, X., & Luo, J. (2026). From anxiety to adaptation: A study on the relationship between college students' AI interaction experience and mental health in higher education. *Acta Psychologica, 269, 107567.* https://doi.org/10.1016/j.actpsy.2026.107567

* Zhang, C. (2026). The relationship between academic self-efficacy and GenAI dependence among college students: a chain mediation model of academic stress and perceived usefulness of GenAI. *Frontiers in Psychology, 17, 1784354.* https://doi.org/10.3389/fpsyg.2026.1784354

* Zhang, S., Zhao, X., Zhou, T., & Kim, J. H. (2024). Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *International Journal of Educational Technology in Higher Education, 21, 34.* https://doi.org/10.1186/s41239-024-00467-0

* Zhang, Z., Kanji, M., Zhang, M., & Zhou, Y. (2026). Learning-oriented generative AI use, self-directed learning, and learning anxiety in higher education: a cross-sectional study. *Frontiers in Education, 11, 1840953.* https://doi.org/10.3389/feduc.2026.1840953

* Zheng, C., & Wang, Y. (2026). Generative AI in EFL contexts: Q-methodological analysis of cognitive dissonance patterns and self-regulation strategies among Chinese tertiary learners. *Acta Psychologica, 264, 106531.* https://doi.org/10.1016/j.actpsy.2026.106531

* Zheng, W., Ratanaolarn, T., & Sriwisathiyakun, K. (2026). A quasi-experimental study of lab rotation integrated with generative AI and peer code review model to enhance students' critical thinking and academic resilience in introductory programming. *Cogent Education, 13(1), 2676265.* https://doi.org/10.1080/2331186x.2026.2676265

* Zhou, C., & Wang, Y. (2026). University Students' Writing Feedback Literacy in the AI Era: The Interplay of Generative AI Acceptance, Writing Anxiety and Writing Self-Efficacy in Chinese EMI Educational Contexts. *European Journal of Education, 61, e70478.* https://doi.org/10.1111/ejed.70478

* Zhu, S., & Hashemifardnia, A. (2026). Investigating a Structured ChatGPT-Assisted Instructional Routine and Its Association with Intolerance of Uncertainty and Emotion Regulation in Higher Education: Insights from Situated Learning Theory. *European Journal of Psychology of Education, 41, 100.* https://doi.org/10.1007/s10212-026-01161-7

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41(2), 64–70.* https://doi.org/10.1207/s15430421tip4102_2

An asterisk (*) identifies each of the 43 reports included in the synthesis. Other entries support methods, theory, or contextual comparison.

Copyright Holder :
© Irsyad, M. F., Damanik, C. M., Marlina, W. A., & Waliyadin, W. (2026).

First Publication Rights:
© Journal of Society Counseling

This article is under:

