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LITERATURE REVIEW ARTICLES

Artificial Intelligence and Student Wellness in Higher Education: A Systematic Review With Implications for Online Graduate Education

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Artificial intelligence (AI) is increasingly being applied as a tool for student wellness. This systematic review of literature examined how AI has been used for student wellness in higher education. It also explored the methodological approaches and the reported evidence for studies of AI and student wellness, as well as how student wellness outcomes have been defined and measured across existing literature. In alignment with PRISMA 2020 guidelines, searches were conducted across the following databases on September 13, 2025: Academic Search Complete, ERIC, Springer Nature, and ScienceDirect. Only empirical studies that focused on higher education students, included an identifiable AI or machine learning (ML) component, and examined a wellness outcome were eligible for inclusion. Of 642 identified records, 56 studies met the criteria for inclusion. The majority of the included studies (75%) were classified as quantitative observational or survey research, and prediction and classification of student wellness concerns was the primary focus of AI use among them. Studies applying experimental, quasi-experimental, or qualitative designs were less common. This article presents the findings of this systematic review, and it provides a foundation for considering how the findings may inform the use of AI to support student wellness in online graduate education. The article also demonstrates the need for more specific research on AI in online graduate education.

Online graduate education provides students with the opportunity to earn an advanced degree while maintaining work and family responsibilities. In their study of 244 online graduate students, Hernández González and Blackford (2022) found that conflicts between work, family, and school roles weakened student engagement and intrinsic motivation. Likewise, Bedford (2024) identified several challenges that online graduate students face while pursuing their degree, such as isolation, stress, and the need to balance their personal life with their academic pursuits. Bedford (2024) called for faculty and institutional support to address the needs of online graduate students and recommended the use of digital tools for support. While these articles were not part of the systematic review, they do demonstrate the importance of recognizing and supporting student wellness in online graduate education (Bedford, 2024; Hernández González & Blackford, 2022).

As artificial intelligence (AI) becomes more widely available, it introduces new opportunities for examining student wellness. In the field of higher education, AI and machine learning have been used to evaluate student mental well-being, stress, suicide risk, fatigue, boredom, and sleep disturbance (Abdul Rahman et al., 2023; Lekkas et al., 2022; Liao et al., 2024; Shen et al., 2020; L. Zhang et al., 2024a). AI has also been explored as a tool for providing direct student support; for instance, He et al. (2022) evaluated an AI mental health chatbot. These studies indicate that AI has a wide range of applications for student wellness.

A systematic review provides an opportunity to see how AI has been applied to student wellness, examine the evidence supporting those applications, and explore how wellness constructs have been defined and measured. The purpose of this systematic review was to examine empirical research on AI and student wellness in higher education. While the review examined literature across the broad field of higher education, the documented wellness and support needs of online graduate students provide a rationale for considering the implications of these findings within online graduate education (Bedford, 2024; Hernández González & Blackford, 2022). For online graduate education, an examination of AI and student wellness in higher education literature provides a basis for considering which applications warrant further study in this population. The following research questions guided this review:

RQ1: How is artificial intelligence used in higher education research related to student mental health and wellness?

RQ2: What methodological approaches are used, and what evidence is reported regarding effectiveness, accuracy, or impact on student mental health and wellness outcomes?

RQ3: What psychological, behavioral, academic, digital, or contextual constructs are examined and operationalized in relation to student mental health and wellness outcomes in higher education AI research?

Methods

The PRISMA 2020 guidelines (Page et al., 2021) were used as a framework to guide the review process. This review was not prospectively registered. No external funding was received for this review, and the author had no competing interests.

Eligibility Criteria

Studies were eligible for inclusion if they met the following criteria: (a) used qualitative, quantitative, or mixed-methods, (b) focused on college or university students, (c) included a clearly identified AI or machine-learning (ML) component, and (d) examined a student wellness outcome. For eligibility purposes, an AI/ML component was considered to be clearly identified when the study described the use of AI or ML technology as part of the research approach, intervention, or application being examined. Searches

were limited to peer-reviewed studies published in English from January 1, 2015, to August 31, 2025. Studies that did not meet these criteria were excluded.

Search Strategy

On September 13, 2025, searches were conducted on four databases: Academic Search Complete (n = 390), ERIC (n = 154), Springer Nature (n = 98), and ScienceDirect (n = 125). The search strategies combined terms pertaining to artificial intelligence and related technologies, mental health and wellness, and higher education populations. Database-specific syntax was applied as appropriate. Although 125 records were initially identified through ScienceDirect, none of those contributed unique records to the dataset following filtering and deduplication. The complete search strings are presented in Appendix A.

Selection Process

All records identified through database searches were imported into Zotero for deduplication and reference management. Duplicate records were removed. Records were screened for eligibility using title and abstract screening, followed by full-text review. The established eligibility criteria were applied at each stage. All title and abstract screening and full-text eligibility decisions were completed by one reviewer. Records that were identified as potentially eligible advanced to full-text review, and reasons for exclusion were documented.

Data Extraction

After the final sample was identified, the data were extracted into a Microsoft Excel spreadsheet. The following predefined fields were applied: study design, AI role, wellness domain, outcome measurement, and key findings. Standardized classifications were applied based on the information presented in the studies and predefined criteria and rules. AI roles were classified based upon the function of AI reported within each study, including prediction/classification or risk modeling, detection/monitoring, intervention/support, and mixed or other applications. Wellness outcomes were classified into three standardized domains: general well-being, mental health, and sleep/fatigue.

The extracted data were organized around the three research questions that guided the review. For RQ1, the role and approach of AI was examined. For RQ2, studies were examined for methodological approach, and reported evidence regarding accuracy, effectiveness, or impact. For RQ3, the wellness constructs and the measures and indicators that were used for those wellness outcomes were identified. Due to the heterogeneity of the studies, findings were synthesized descriptively rather than through meta-analysis. Data extraction and analysis were completed by one reviewer. The completed data set was reviewed against the source articles to check accuracy and consistency of the extracted information and classifications. A formal risk

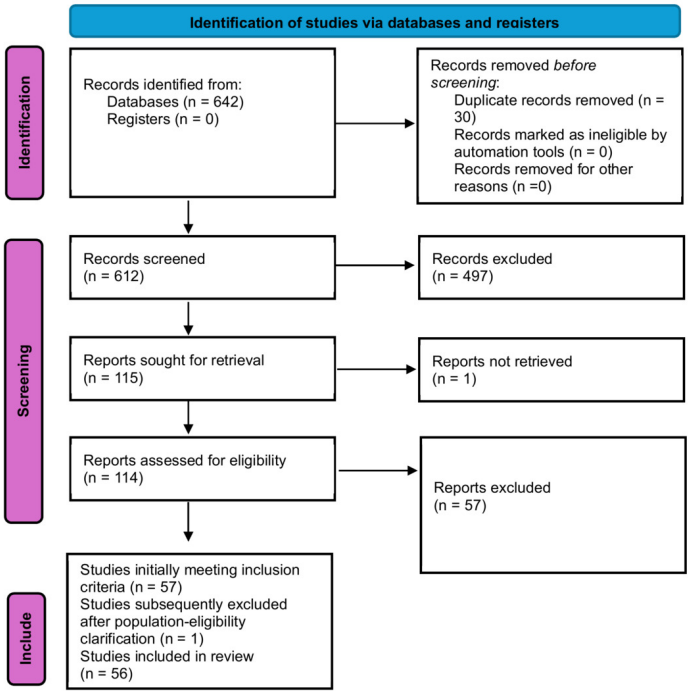


Figure 1. PRISMA 2020 Flow Diagram of Study Identification and Selection

Note. Adapted from the PRISMA 2020 flow diagram (Page et al., 2021), licensed under CC BY 4.0.

of bias assessment for individual studies was not conducted. The review was designed to descriptively examine how AI has been studied in relation to student wellness across a heterogeneous body of research rather than to evaluate the comparative quality or certainty of evidence across studies.

Results

Study Selection

The database searches identified 642 records. Following the removal of 30 duplicate records, 612 records underwent title and abstract screening, of which 497 were excluded. Of the 115 reports identified for full-text retrieval, one could not be retrieved, leaving 114 reports for full-text review. Following full-text review, 57 studies were excluded, and 57 initially met the inclusion criteria. One study was subsequently excluded following clarification of population eligibility, resulting in a final sample of 56 studies. The study selection process is presented in the PRISMA 2020 flow diagram (Figure 1).

Characteristics of Included Studies

The 56 studies that were included in this review represented a range of higher education populations, methodological approaches, AI applications, and student wellness outcomes. The characteristics of the individual studies that were included in this review are presented in Appendix B.

Table 1. Standardized Study Types of Included Studies (N = 56)

Study Type	***n***	**%**
Quantitative observational/survey	42	75.0
Quantitative experimental	5	8.9
Quantitative quasi-experimental	3	5.4
Mixed methods	5	8.9
Qualitative	1	1.8
Total	**56**	**100.0**

AI Roles and Applications (RQ1)

The included studies examined the use of AI across several roles in student wellness. Prediction and classification of student well-being using AI or ML models were common applications (Abdul Rahman et al., 2023). AI was also used for student stress (Liao et al., 2024; Rois et al., 2021), depression (Siraji et al., 2023; Teng et al., 2024), suicide risk (Macalli et al., 2021; Naghavi et al., 2020; Shen et al., 2020), and sleep disturbance (L. Zhang et al., 2024a). Other studies combined AI and behavioral or digital data; for instance, Lekkas et al. (2022) analyzed smartphone data in models predicting student fatigue and boredom.

AI was also explored as a tool for student wellness support and intervention. Both He et al. (2022) and Qi (2025) studied chatbots for students with depressive symptoms. Among college students, AI interventions were also studied for speaking anxiety (El Shazly, 2021), loneliness (Lu & Guo, 2025), psychological well-being (C. Wang et al., 2025), and emotional well-being (Zong & Yang, 2025).

Methodological Approaches and Reported Evidence (RQ2)

Of the 56 studies, 42 were classified as quantitative observational or survey research (75%). Quantitative experimental designs accounted for five studies (8.9%), and three (5.4%) were classified as quantitative quasi-experimental studies. Five studies (8.9%) applied mixed methods, and one study (1.8%) was qualitative. The standardized study types are presented in Table 1.

Within these broad methodological categories, studies used research designs such as cross-sectional surveys, secondary data analyses, experimental designs, and many also applied predictive AI or ML modeling. Predictive studies often reported on model performance. For example, Shen et al. (2020) reported area under the curve (AUC) of 0.93 for a random forest model that was used to identify suicide risk among Chinese medical students.

The studies that evaluated AI interventions for student wellness focused more on changes in wellness outcomes rather than model performance. For example, He et al. (2022) evaluated changes in student depressive symptoms during a randomized controlled trial of an AI mental health chatbot. The quasi-experimental study by Qi (2025) examined student depressive

Table 2. Student Wellness Domains Examined Across Included Studies (N = 56)

Wellness Domain	***n***	**%**
Mental health	28	50.0
General well-being	26	46.4
Sleep/fatigue	2	3.6
Total	**56**	**100.0**

symptoms and an AI "Woebot" intervention. Across the 56 studies, the application of AI to student wellness, and the methodological approaches used to examine them varied.

Wellness Constructs and Outcomes (RQ3)

Multiple dimensions of student wellness were identified in the literature. Through application of standardized wellness-domain classifications, the following were identified: mental health (n = 28), general well-being (n = 26), and sleep/fatigue (n = 2). Mental health was used to classify studies pertaining to clinical depression, clinical anxiety, suicidality, and burnout. General well-being was used to classify non-clinical wellness constructs ranging from non-clinical emotional well-being, such as stress, to student motivation and resilience. Sleep and fatigue made up the smallest portion of the student wellness outcomes presented in the studies. Table 2 presents the student wellness domains that were identified in the review of literature.

Across the literature in the review, student wellness outcomes were evaluated using a variety of measures; for example, some studies used established scales to assess depression, anxiety, stress, and psychological well-being (He et al., 2022; Pereira et al., 2025). Some predictive studies used model-performance metrics, such as accuracy, area under the curve (AUC), sensitivity, specificity, and F1 scores, to evaluate the performance of AI or ML models (Naghavi et al., 2020; Shen et al., 2020; L. Zhang et al., 2024a). Other studies applied behavioral or digital indicators, such as smartphone use or sensor data (Lekkas et al., 2022; Liao et al., 2024). Kohnke and Moorhouse (2025) used semi-structured interviews to examine student motivation, anxiety, stress, and emotional wellness through generative AI support.

Discussion

This systematic review of literature examined how AI has been used for student wellness in higher education, the methodological approaches and evidence reported in the studies, and how student wellness was defined and measured. The review findings indicate that AI has been studied across a wide range of student wellness concerns and applications in higher education; however, the nature of the available evidence varies considerably. The following discussion of the findings is organized according to the three research questions, followed by the implications for online graduate education.

AI Roles and Applications

The first research question examined how AI is currently being used for student wellness. Across the included studies, AI was applied to a broad range of student wellness outcomes and roles. These applications included predicting or classifying student wellness outcomes such as depression, suicide risk, stress, and sleep disturbance, as well as analyzing behavioral or digital data related to fatigue and boredom (Lekkas et al., 2022; Liao et al., 2024; Macalli et al., 2021; Shen et al., 2020; Siraji et al., 2023; Teng et al., 2024; L. Zhang et al., 2024a). Other studies examined AI-supported interventions or services, including mental health chatbots and intelligent academic advising (El-kholy, 2025; He et al., 2022; Qi, 2025).

These findings illustrate an important element of how AI is being studied in higher education, and they highlight an important area for consideration. Using AI to predict or identify a wellness concern differs from using AI to provide student support in response to that concern. For instance, an AI model that identifies students who are at risk for depression differs from a chatbot that provides support for students with depressive symptoms. It is important for universities to recognize these distinctions when evaluating the potential applications of AI.

For online graduate education, this distinction provides a useful way to consider how AI might contribute to student wellness. AI applications that identify or predict wellness concerns serve different functions than applications that are designed to provide direct student support. Some programs may benefit more from applications that identify and predict student wellness concerns, while other programs may choose to concentrate more on AI support interventions that online students can access. Online graduate programs should consider the specific needs of online graduate students and the intended role of the AI when evaluating potential AI applications.

Methodological Approaches

The second research question (RQ2) examined the methodological approaches used to study AI and student wellness and the reported accuracy, effectiveness, or impact of the AI applications. Quantitative observational or survey research accounted for 75% of the studies. Experimental and quasi-experimental studies were less common, and only one study was qualitative. The methods used are important in interpreting the findings of the studies and in identifying areas where further research is needed.

Much of the literature focused on how AI can be used to identify or predict student wellness. For instance, there were studies that evaluated how well AI or ML applications predicted suicide risk (Macalli et al., 2021; Naghavi et al., 2020; Shen et al., 2020). These findings provide valuable information about the performance of these models; however, model performance studies do not necessarily establish whether the AI models result in improvements in student wellness outcomes.

A smaller portion of the literature focused on AI interventions and student wellness outcomes. He et al. (2022) noted reductions in student depressive symptoms in a randomized controlled trial of a mental health chatbot. Qi (2025) noted some reduction in mild depressive symptoms following students interacting with their "Woebot," which was also an AI chatbot. El-kholy (2025) found that postgraduate students experienced increased satisfaction and reduced stress after using an AI advising system. These studies focus more on the student wellness outcomes following AI intervention than studies of predictive model performance. This distinction is also important for the field of online graduate education. Before applying AI to student wellness support, programs should consider whether there is established evidence that the AI application can identify a wellness concern and whether the existing literature has examined its effects on student wellness outcomes.

Overall, the literature focuses more heavily on AI prediction of student wellness constructs than on how AI supports student wellness. Additional experimental, quasi-experimental, longitudinal, and qualitative research would provide a wider range of evidence for understanding AI and student wellness. Further studies on AI interventions and student wellness outcomes are also needed.

Wellness Constructs

The third research question examined how student wellness constructs were presented and measured across the literature. Student wellness constructs varied considerably across the included studies. Depression, anxiety, stress, suicidality, burnout, psychological and emotional well-being, resilience, fatigue, boredom, and sleep disturbances are examples of student wellness constructs that were presented in the included studies (Abdul Rahman et al., 2023; Lekkas et al., 2022; Rois et al., 2021; Shen et al., 2020; Teng et al., 2024; L. Zhang et al., 2024b). The included studies reflect considerable variation in how student wellness was defined in the literature. The approaches that were used to measure these wellness constructs also varied considerably. Some studies used established scales to assess depression, anxiety, stress, or psychological well-being (He et al., 2022; Pereira et al., 2025). Several predictive studies of model performance presented the accuracy, area under the curve, sensitivity, specificity, and F1 scores of the AI or ML models (Naghavi et al., 2020; Shen et al., 2020; L. Zhang et al., 2024a). Other studies focused on behavioral or digital indicators of student wellness, such as information from smartphone use or sensor data (Lekkas et al., 2022; Liao et al., 2024). A qualitative study provided another perspective of student wellness by examining the student experience with AI learning and emotional support interventions (Kohnke & Moorhouse, 2025).

The variation in the wellness constructs and how they were measured are important considerations when determining how AI can be used for student wellness and what further research is needed. Studies of how well an AI model identifies or predicts a student wellness outcome provide useful information on the specific models and wellness constructs that they study;

however, they do not answer how students experience AI wellness support or how AI interventions affect student wellness. Future studies should distinguish between AI or ML model performance studies and studies of AI wellness support and interventions.

For online graduate education, these findings suggest that student wellness must be clearly defined when considering AI applications. Different wellness concerns, such as stress, depression, fatigue, or general well-being, may require different AI approaches for identification, measurement, and student support; thus, clarifying the wellness needs of online graduate students is an important first step.

Implications for Online Graduate Education

This systematic review of literature evaluated 56 included studies across the broader field of higher education; however, much of the information on AI and student wellness is relevant to online graduate education. To frame these findings within the scope of online graduate education, two additional studies specific to online graduate students were considered separately from the systematic review. Bedford (2024) and Hernández González and Blackford (2022) identified the challenges that online graduate students face when balancing their academic, professional, and personal responsibilities. The authors also emphasized the importance of academic and emotional support for online graduate students (Bedford, 2024; Hernández González & Blackford, 2022). The AI applications that were identified in this systematic review may offer additional ways for programs to recognize needs and provide support for online graduate students.

One important consideration is the intended role of AI in student wellness. This review identified applications that predicted or classified student wellness concerns, as well as applications that provided direct student support. Predictive applications can help online graduate programs identify student wellness concerns, while intervention and support applications may provide additional ways for students to obtain assistance. Online graduate programs should distinguish between predictive model performance and evidence of effectiveness in supporting student wellness when considering AI applications.

The findings also indicate the importance of clearly identifying wellness concerns that AI applications are intended to address. The studies examined a wide range of wellness constructs using different measures and indicators; however, further research is needed to specifically explore AI and student wellness in online graduate education, including research that evaluates student wellness outcomes and experiences with AI wellness interventions.

Limitations

There are several limitations that should be considered when interpreting the findings of this systematic review of literature. The research methods, AI applications, and wellness constructs varied considerably across the included studies. This variance limited comparison across studies; therefore, the

findings were synthesized descriptively rather than through meta-analysis. Quantitative observational or survey research dominated the literature, with few quasi-experimental, experimental, and qualitative studies. The literature focused more extensively on the ability of AI to identify or predict wellness outcomes than on whether AI applications improve student wellness. Future studies of AI and student wellness may find it helpful to focus more specifically on AI interventions for student wellness.

The literature searches were conducted across four academic databases and did not include supplementary reference list searching; thus, they may not have identified all available studies. The review was also conducted by a single reviewer, which increases the potential for error or bias during study selection, data extraction, and classification. Several steps were taken to mitigate error or bias, including predefined inclusion and exclusion criteria, structured data extraction, standardized coding categories, rule-based classification, documented reasons for full-text exclusion, automatic and manual deduplication, and quality control review of the completed dataset. A formal risk of bias assessment of the included studies was not conducted; therefore, the findings should not be interpreted as an assessment of study quality or certainty of evidence. The review was also not prospectively registered.

While the literature included in the systematic review did include some studies of graduate and postgraduate students, the review was not specific to online graduate education (El-kholy, 2025; Lekkas et al., 2022; Teng et al., 2024). Some of the findings on AI and student wellness are relevant to online graduate education; however, further research on AI and student wellness in online graduate education is needed.

Conclusion

This systematic review of literature examined 56 studies of AI and student wellness across the field of higher education. The findings demonstrate that AI has many potential applications, including identifying and predicting wellness concerns and providing support and interventions for student wellness. The literature predominantly used quantitative observational or survey methods, with fewer studies directly evaluating the impact or experience of AI. The findings indicate that AI was frequently used to identify or predict student wellness concerns; however, fewer studies examined whether these applications improve student wellness outcomes.

The present review identifies how AI is being used to identify and support student wellness in higher education. Other studies have established the challenges that students experience and called for academic and emotional support for students in online graduate education (Bedford, 2024; Hernández González & Blackford, 2022). Together, these studies provide a foundation for considering how AI might contribute to identifying and supporting student wellness in online graduate education. Further research into AI, student wellness, and online graduate education is needed to

determine how AI applications can best support student wellness in this population. The data supporting this systematic review are reported within the article and its appendices.

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Appendices

Appendix A

Complete Database Search Strategies

Searches were limited to peer-reviewed studies published in English from January 1, 2015 to August 31, 2025.

ERIC (09/13/25; *n* = 154):

("artificial intelligence" OR AI OR "machine learning" OR "chatbot*" OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*")
AND (wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support")
AND ("higher education" OR universit* OR college* OR "postsecondary" OR "graduate student*" OR "doctoral student*" OR faculty OR professor*)

Academic Search Complete (09/13/25; n = 390):

(TI("artificial intelligence" OR "machine learning" OR chatbot* OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*")
OR AB("artificial intelligence" OR "machine learning" OR chatbot* OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*")
OR SU("artificial intelligence" OR "machine learning" OR chatbot* OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*"))
AND (TI(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support")
OR AB(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support")
OR SU(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support"))
AND (TI("higher education" OR universit* OR college* OR postsecondary OR "graduate student*" OR "doctoral student*" OR faculty OR professor*)
OR AB("higher education" OR universit* OR college* OR postsecondary OR "graduate student*" OR "doctoral student*" OR faculty OR professor*)
OR SU("higher education" OR universit* OR college* OR postsecondary OR "graduate student*" OR "doctoral student*" OR faculty OR professor*))

ScienceDirect (09/13/25; n = 125; 0 retained after filtering):

TITLE-ABSTR-KEY("artificial intelligence" OR AI OR "machine learning" OR "chatbot*" OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*")
AND TITLE-ABSTR-KEY(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support")

AND TITLE-ABSTR-KEY("higher education" OR universit* OR college* OR "postsecondary" OR "graduate student*" OR "doctoral student*" OR faculty OR professor*)

Springer Nature (09/13/25; n = 98):

(title:("artificial intelligence" OR AI OR "machine learning" OR "chatbot*" OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*")
OR abstract:("artificial intelligence" OR AI OR "machine learning" OR "chatbot*" OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*")
OR keyword:("artificial intelligence" OR AI OR "machine learning" OR "chatbot*" OR "conversational agent*" OR "predictive analytics" OR "virtual coach*" OR "digital mental health" OR "wellness app*"))
AND (title:(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support")
OR abstract:(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support")
OR keyword:(wellness OR "mental health" OR "well-being" OR stress OR burnout OR resilience OR "emotional support"))
AND (title:("higher education" OR universit* OR college* OR "postsecondary" OR "graduate student*" OR "doctoral student*" OR faculty OR professor*)
OR abstract:("higher education" OR universit* OR college* OR "postsecondary" OR "graduate student*" OR "doctoral student*" OR faculty OR professor*)
OR keyword:("higher education" OR universit* OR college* OR "postsecondary" OR "graduate student*" OR "doctoral student*" OR faculty OR professor*))

Appendix B

Characteristics of Included Studies

Table B1. Characteristics of Studies Included in the Systematic Review

Study	Country	Population	Study Type	AI Role	Wellness Domain
Saif et al. (2024)	Pakistan	Discipline-specific students	Quantitative observational/ survey	Support/Adoption	General well-being
Lekkas et al. (2022)	Netherlands	Graduate students	Quantitative observational/ survey	Prediction	General well-being
He et al. (2022)	China	University students (unspecified)	Quantitative, Experimental	Intervention / Support	Mental health
Shen et al. (2020)	China	Discipline-specific students	Quantitative observational/ survey	Prediction	Mental health
Rasouli et al. (2024)	Canada	Undergraduate students	Quantitative observational/ survey	Intervention / Support	Mental health
Naghavi et al. (2020)	Iran	Mixed undergraduate/ graduate	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Zhang et al. (2024a)	China	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Sleep / Fatigue
Abdul Rahman et al. (2023)	Southeast Asia (ASEAN)	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Mamun et al. (2025)	Bangladesh	Mixed undergraduate/ graduate	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Erdemir & Atik (2025)	Turkey	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Kohnke & Moorhouse (2025)	China (Hong Kong SAR)	University students (unspecified)	Qualitative	Intervention / Support	General well-being
Wang, Wang, et al. (2025)	China	University students (unspecified)	Quantitative, Quasi-experimental	Intervention / Support	General well-being
Byers et al. (2023)	United States	University students (unspecified)	Mixed Methods	Predict / Classify / Risk Stratification	Mental health
Wang & Kang (2025)	China	Undergraduate students	Quantitative, Experimental	Detect / Monitor	Mental health
Guo et al. (2024)	China	Undergraduate students	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Huang et al. (2024)	China	Mixed undergraduate/ graduate	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Zhao (2022)	China	Undergraduate students	Quantitative, Experimental	Predict / Classify / Risk Stratification	Mental health
Macalli et al. (2021)	France	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
El Shazly (2021)	Egypt	University students (unspecified)	Mixed Methods	Intervention / Support	General well-being
Nooripour et al. (2024)	Iran	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Liao et al. (2024)	United States	University students (unspecified)	Quantitative observational/	Predict / Classify / Risk Stratification	General well-

Study	Country	Population	Study Type	AI Role	Wellness Domain
			survey		being
Zhou et al. (2021)	China	University students (unspecified)	Quantitative observational/ survey	Detect / Monitor	General well-being
Sara et al. (2024)	Bangladesh	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Mamun & Al-Mamun (2025)	Bangladesh	University students (unspecified)	Quantitative observational/ survey	Prediction / risk modeling	Mental health
Rois et al. (2021)	Bangladesh	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Siraji et al. (2023)	Bangladesh	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Kong et al. (2025)	China	Undergraduate students	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Sanchez-Trigo et al. (2024)	Spain	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Sleep / Fatigue
Jin et al. (2025)	China	Discipline-specific students	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Zhao et al. (2022)	United States	Mixed undergraduate/ graduate	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Hanani et al. (2024)	Palestine	Discipline-specific students	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Dagani et al. (2024)	Italy	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Deivasigamani et al. (2025)	Malaysia	Discipline-specific students	Quantitative observational/ survey	Prediction	Mental health
Lotfi et al. (2025)	Serbia	University students (unspecified)	Quantitative observational/ survey	Detect / Monitor	Mental health
Pereira et al. (2025)	Portugal	Mixed undergraduate/ graduate	Quantitative observational/ survey	Other / Mixed AI role	Mental health
Shi et al. (2025)	China	Mixed undergraduate/ graduate	Quantitative observational/ survey	Predict / Classify / Risk Stratification	General well-being
Noreen et al. (2025)	Pakistan	Graduate students	Quantitative observational/ survey	Other / Mixed AI role	Mental health
Thity et al. (2025)	Bangladesh	University students (unspecified)	Quantitative observational/ survey	Predict / Classify / Risk Stratification	Mental health
Qi (2025)	China	Discipline-specific students	Quantitative, Quasi-experimental	Intervention / Support	Mental health
Zhang et al. (2025)	China	University students (unspecified)	Quantitative observational/ survey	Other / Mixed AI role	Mental health
Lu et al. (2025)	China	University students (unspecified)	Quantitative, Experimental	Intervention	Mental health

Study	Country	Population	Study Type	AI Role	Wellness Domain
Teng et al. (2024)	International	Graduate students	Quantitative observational/ survey	Other / Mixed AI role	Mental health
Zhang et al. (2024b)	China	University students (unspecified)	Quantitative observational/ survey	Other / Mixed AI role	Mental health
Al-Zahrani (2025)	Saudi Arabia	University students (unspecified)	Quantitative observational/ survey	Other / Mixed AI role	General well-being
Wang, Richmond, et al. (2025)	United States	University students (unspecified)	Quantitative observational/ survey	Prediction / risk modeling	Mental health
Al-Azzam & Al-Oudat (2025)	Jordan	University students (unspecified)	Quantitative observational/ survey	Prediction / risk modeling	General well-being
Wolgast & Bieletzke (2025)	Germany	University students (unspecified)	Quantitative observational/ survey	Monitoring	General well-being
Song (2025)	China	Discipline-specific students	Quantitative observational/ survey	Support/Adoption	General well-being
El-kholy (2025)	Egypt	Graduate students	Quantitative, Quasi-experimental	Intervention	General well-being
Zong & Yang (2025)	China	Mixed students (undergraduate + graduate)	Quantitative observational/ survey	Support/ Intervention	General well-being
Lai (2025)	Taiwan	Undergraduate students	Mixed Methods	Intervention	General well-being
Sayed et al. (2024)	Ethiopia	University students (unspecified)	Mixed Methods	Intervention	General well-being
Long & Lin (2024)	China	Discipline-specific students	Quantitative observational/ survey	Monitoring	Mental health
Çakmak (2022)	Turkey	Undergraduate students	Mixed Methods	Intervention	General well-being
Xu & Xu. (2024)	China	Discipline-specific students	Quantitative, Experimental	Intervention	General well-being
Lin et al. (2024)	Taiwan	University students (unspecified)	Quantitative observational/ survey	Machine learning – prediction	Mental health

Note. Study characteristics are reported using the standardized classifications in the frozen extraction dataset.