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UNIVERSIDAD ESTATAL DE MILAGRO

REPÚBLICA DEL ECUADOR

UNIVERSIDAD ESTATAL DE MILAGRO
FACULTAD DE POSGRADO

VICERRECTORADO DE INVESTIGACIÓN Y POSGRADO

ARTÍCULOS PROFESIONALES DE ALTO NIVEL
PREVIO A LA OBTENCIÓN DEL TÍTULO DE:

MAGÍSTER EN INTELIGENCIA ARTIFICIAL PARA LA EDUCACIÓN

TEMA:

AI-DRIVEN PREDICTIVE MODELS AND CHATBOTS FOR EARLY
INTERVENTION AND STUDENT SUCCESS IN HIGHER EDUCATION: A
SYSTEMATIC REVIEW

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Milagro, año 2026

AI-Driven Predictive Models and Chatbots for Early Intervention and Student Success in Higher Education: A Systematic Review*

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Student attrition in higher education remains a persistent global issue, with dropout rates exceeding 40% in several countries. This necessitates the development of early evidence-based intervention strategies. Artificial Intelligence (AI) has emerged as a promising tool; however, its implementation is often approached in a fragmented manner. This systematic review analyzes the synergistic use of machine learning-based predictive models and conversational chatbots as an integrated system to support students' success. A total of 46 studies indexed in Scopus, Web of Science, and IEEE Xplore (2019–2024) were examined according to the PRISMA 2020 protocol. The results indicate that techniques such as neural networks and random forests achieve predictive accuracies above 90% for academic risk detection, with hybrid models reaching F1 scores of up to 0.99. Concurrently, chatbots are evolving into personalized virtual tutors with contextual response capabilities and 24/7 availability, achieving F1 = 99.75% and boosting academic performance by 25%. The integration of these technologies has a positive impact on student retention, motivation, and institutional efficiency. The future of support systems lies in integrated, ethical, pedagogically grounded, and student-centered AI ecosystems that can transform educational interventions into more inclusive and effective environments.

Keywords: conversational chatbots; dropout prediction; early intervention; educational artificial intelligence; higher education; machine learning; predictive models; student success

La deserción estudiantil en la educación superior sigue siendo un problema global persistente, con tasas de abandono que superan el 40% en varios países. Esto requiere el desarrollo de estrategias de intervención temprana basadas en evidencia. La Inteligencia Artificial (IA) ha surgido como una herramienta prometedora; sin embargo, su implementación a menudo se aborda de manera fragmentada. Esta revisión sistemática analiza el uso sinérgico de modelos predictivos basados en aprendizaje automático y chatbots conversacionales como un sistema integrado para apoyar el éxito de los estudiantes. Se examinaron un total de 46 estudios indexados en Scopus, Web of Science e IEEE Xplore (2019–2024) según el protocolo PRISMA 2020. Los resultados indican que técnicas como redes neuronales y bosques aleatorios logran precisiones predictivas superiores al 90% para la detección de riesgo académico, con modelos híbridos que alcanzan puntuaciones F1 de hasta 0.99. Concurrentemente, los chatbots están evolucionando hacia tutores virtuales personalizados con capacidades de respuesta contextual y disponibilidad 24/7, logrando F1=99.75% y aumentando el rendimiento académico en un 25%. La integración de estas tecnologías tiene un impacto positivo en la retención estudiantil, la motivación y la eficiencia institucional. El futuro de los sistemas de apoyo radica en ecosistemas de IA integrados, éticos, fundamentados pedagógicamente y centrados en el estudiante que pueden transformar las intervenciones educativas en entornos más inclusivos y efectivos.

Palabras clave: chatbots conversacionales; predicción de deserción; intervención temprana; inteligencia artificial educativa; educación superior; aprendizaje automático; modelos predictivos; éxito estudiantil.

1. Introduction

Within the framework of the digital transformation of education, often referred to as Education 4.0, student dropout in higher education remains a persistent global challenge, with profound implications for equity, human capital development, and the sustainability of educational systems. In numerous countries, a significant proportion of students leave university without earning a degree, particularly in the early years of their academic programs.

The data are compelling: in the United States, it is estimated that 39% of full-time college students do not complete their degrees within an eight-year

period, and approximately 23.3% drop out during their first year [1]. In Latin America, dropout rates are also high, exceeding 50% in Colombia [2] and approaching 40% in Ecuador, where attrition is concentrated mainly in the early semesters [3]. In Europe, countries such as Spain and Italy also face this issue; for instance, in Andalusia, approximately 27.5% of students discontinued the degree program they began, while in Italy, the national dropout rate between the first and second years reached 12.2% [4, 5].

Despite their regional specificities, these figures reflect common patterns associated with academic, economic, institutional and psychosocial factors.

57 Consequently, the development of early interven-

tion strategies is imperative to identify at-risk 29
students and provide them with effective support, 30
thereby preventing dropout from becoming a defi- 31
nitive decision [6, 7]. 32

Higher education institutions are increasingly 33
turning to Artificial Intelligence (AI) as a catalyst 34
for innovation (Ghosh et al., 2024), not only to 35
optimize administrative processes but also to trans- 36
form the learning experience through the persona- 37
lization of educational pathways [8]. 38

Within the broad spectrum of AI applications, 39
two technologies have gained particular promi- 40
nence as cornerstones of comprehensive interven- 41
tion strategies: machine learning (ML)-based 42
predictive models and conversational chatbots. 43
These two technologies are analyzed jointly as 44
they represent two synergistic and complementary 45
phases of student support: risk identification and 46
scalable intervention. 47

First, ML techniques, including decision trees, 48
neural networks, and deep learning, were used to 49
develop early warning systems. These systems ana- 50
lyze large volumes of historical data, such as aca- 51
demic performance, interactions within Learning 52
Management Systems (LMS), and demographic 53
variables, to accurately predict which students may 54
require additional support [9, 10]. The ability of these 55
techniques to process complex nonlinear data struc- 56
tures has proven superior to that of traditional 57

1 statistical methods [11], achieving prediction accura-
2 cies of up to 96% using hybrid models [12–14].

3 Once an at-risk student is identified, intelligent
4 chatbots emerge as a scalable and personalized
5 intervention tool. The advent of generative AI,
6 exemplified by the launch of ChatGPT, marks a
7 turning point and demonstrates an unprecedented
8 adoption rate [15].

9 These conversational agents simulate natural
10 dialogue to provide 24/7 academic and administra-
11 tive support [16]. Acting as virtual tutors, they can
12 answer questions, offer formative feedback, and
13 adapt task difficulty in accordance with pedagogical
14 principles, such as constructivist learning and cog-
15 nitive load theory [17–19].

16 For teaching staff, chatbots automate repetitive
17 tasks, freeing time to focus on cases that require
18 deeper human interaction [20–22]. Empirical evi-
19 dence suggests that their integration can increase
20 student participation and engagement [23], with a
21 positive, albeit modest, impact on academic perfor-
22 mance [24].

23 Despite the vast potential of the synergy between
24 predictive analytics and conversational AI, their
25 implementation is not without challenges. Predic-
26 tive models face the risk of algorithmic bias inher-
27 ited from historical data, as well as a “black box”
28 nature that hinders the interpretability of their
29 outputs for pedagogical purposes, thus demanding
30 a focus on fairness and explainability [25–27].

31 Conversely, chatbots raise concerns regarding
32 academic integrity [28], the potential spread of
33 misinformation [29], data privacy, and possible
34 erosion of students’ critical thinking skills [15].
35 Furthermore, it is essential to recognize that tech-
36 nological support should not replace genuine
37 human interaction, which is critical for fostering a
38 sense of belonging [30, 31].

39 Although some studies have examined predictive
40 models and chatbots in isolation, there remains a
41 gap in the literature synthesizing evidence on their
42 combined use as an integrated early intervention
43 system. A comprehensive perspective is needed that
44 critically analyzes how these two facets of AI can be
45 effectively and ethically integrated to promote stu-
46 dent success in higher education settings.

47 Accordingly, this systematic literature review
48 aims to identify, describe, and critically analyze
49 strategies employing ML-based predictive models
50 and AI-driven chatbots, as reported in high-impact
51 literature from 2019 to 2024. Specifically, this study
52 seeks to address the following research questions:

- 53
54 1. Which machine learning techniques are most
55 commonly used to predict dropout risk or low
56 academic performance, and what levels of
57 accuracy have been reported in the literature?

2. What are the technical (e.g., natural language
capabilities and underlying algorithms) and
pedagogical (e.g., types of feedback, adaptabil-
ity, and engagement level) features of educa-
tional chatbots used as intervention tools?

3. What measurable impact do these technologies
have on key indicators, such as academic
performance, motivation, and student reten-
tion rates?

10
11 Unlike prior reviews that focus exclusively on
12 predictive models or conversational agents in iso-
13 lation – often lacking a unifying theoretical frame-
14 work or a joint assessment of the intervention cycle
15 – this study offers a dual-level critical synthesis of
16 both technical and pedagogical aspects. It addresses
17 two recurring limitations in the literature: (i) an
18 excessive focus on accuracy metrics without ade-
19 quate consideration of model explainability and
20 fairness, and (ii) insufficient attention to the align-
21 ment between chatbot functionalities and learning
22 theories. By integrating these dimensions into a
23 single analysis, this review not only provides an
24 up-to-date thematic mapping but also offers a
25 comprehensive framework for rethinking the role
26 of AI in building ethical, effective, and learning-
27 centered student support systems.

28 29 30 **2. Methodology**

31 This study was conducted through a systematic
32 literature review (SLR) in accordance with the
33 methodological principles established by
34 PRISMA 2020 [32] to ensure transparency, trace-
35 ability, and reproducibility of the review process.
36 This approach was chosen because of its capacity to
37 integrate findings in a structured, critical, and
38 rigorous manner, particularly in interdisciplinary
39 fields such as higher education mediated by emer-
40 ging technologies. Additionally, recommendations
41 [33] were considered, highlighting the value of
42 systematic reviews as a research strategy in contexts
43 where educational theories, digital innovation and
44 impact analysis converge. The technical guidelines
45 proposed by [34], which are widely recognized in the
46 fields of engineering and educational computing,
47 were also incorporated to strengthen the protocol’s
48 robustness. The process was structured into five
49 phases: (i) protocol formulation, (ii) literature
50 search, (iii) screening and selection of studies, (iv)
51 data extraction and coding, and (v) qualitative
52 thematic analysis.

53 54 *2.1 Search Strategy*

55 The search strategy was designed through an itera-
56 tive process of semantic refinement, guided by the
57 principles of sensitivity (capturing the broadest

possible range of relevant studies) and specificity (excluding irrelevant results), in accordance with the best practices for systematic reviews in interdisciplinary contexts [33–35]. Four thematic groups were defined to reflect the core components of the research focus: (i) predictive analytics techniques, (ii) educational intervention technologies, (iii) outcomes related to student success, and (iv) the higher education context.

Terms within each group were combined using the Boolean operator OR, and the groups were integrated using AND to balance the comprehensiveness and precision. The selection of specific terms was based on an exploratory review of the key literature identified during preliminary searches, considering both author-provided keywords and indexed descriptors from the Scopus, Web of Science, and IEEE Xplore databases. Patterns of co-occurrence and frequent synonyms were analyzed to ensure adequate semantic coverage of the field, as shown in Table 1.

Moreover, the search string was reviewed by two experts in educational technology and learning analytics, who validated its conceptual coherence and proposed adjustments to enhance the precision of the result retrieval. A pilot search was also conducted using a random subset of records to assess thematic relevance and apply minor refinements aimed at reducing ambiguity or overlap. The final search string, adapted to the specific query fields of each database (TS in Web of Science, TITLE-ABS-KEY in Scopus, and All Metadata in IEEE Xplore), is presented below.

2.2 Final Search String

The final search string used across the three databases was as follows:

((“predictive model” OR “machine learning” OR “early warning system” OR “artificial intelligence” OR “deep learning”) AND (“chatbot*” OR “conversational agent*” OR “AI tutor*” OR “personalized learning*”) AND (“student success” OR “academic performance” OR dropout OR retention OR risk OR “student support”) AND (“higher education” OR universit*)) AND PY = [2019–2024]

Table 1. Groups of Terms Used in the Search String

Group	Thematic Focus	Terms Included
1	Predictive analytics techniques	“predictive model” OR “machine learning” OR “early warning system” OR “artificial intelligence” OR “deep learning”
2	Educational intervention technologies	“chatbot*” OR “conversational agent*” OR “AI tutor*” OR “personalized learning*”
3	Educational outcomes	“student success” OR “academic performance” OR dropout OR retention OR risk OR “student support”
4	Educational context	“higher education” OR universit*

The search was limited to documents published between 2019 and 2024, with the aim of including recent studies related to AI-based predictive models and conversational agents, particularly following the emergence of generative artificial intelligence in educational contexts. Filters were also applied to restrict the results to peer-reviewed journal articles and conference proceedings published primarily in English, given their predominance in the international scientific output in this field.

2.3 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were defined a priori and systematically applied during the screening phase, in accordance with the methodological recommendations of the PRISMA framework. These criteria were established to ensure the thematic relevance, methodological quality, and contextual pertinence of the selected studies, in accordance with the objectives of this systematic review.

Only documents published between 2019 and 2024 were included to capture recent developments in the application of artificial intelligence, particularly predictive models and conversational agents in higher education during a period marked by the rise of generative AI.

In addition, only publications in English were considered, as it is the predominant language in international scientific literature and the selected databases (Scopus, Web of Science, and IEEE Xplore).

From a methodological standpoint, only original research articles and peer-reviewed conference proceedings were accepted, whereas grey literature, theses, previous systematic reviews, technical reports, editorials, and short communications were excluded.

In thematic terms, the studies were required to meet the following criteria:

- (i) The use of machine learning techniques or artificial intelligence (AI) tools to predict academic performance or risk has been previously addressed.
- (ii) Intelligent conversational agents (chatbots, virtual tutors, and AI assistants) are included as a

Table 2. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication Year	2019–2024	Publications prior to 2019 or after 2024.
Language	English	Other languages
Document Type	Peer-reviewed research articles and conference proceedings	Theses, grey literature, reviews, editorials, non-reviewed abstracts
Peer Review	Yes	No
Educational Context	Higher education	Other educational levels (primary, secondary, informal)
Technology Addressed	Machine learning models and/or conversational agents	Non-predictive and non-conversational technologies
Outcome Variable	Student success indicators (e.g., performance, retention, motivation, etc.)	Absence of outcomes related to student success or dropout

strategy for personalized educational interventions.

(iii) It is contextualized within higher education environments.

(iv) Empirical results related to indicators of student success, such as academic performance, retention, dropout, motivation, and engagement were reported.

Table 2 summarizes the inclusion and exclusion criteria of this review.

2.4 Screening and Study Selection Process

The screening process was conducted in multiple stages to ensure strict adherence to the predefined inclusion criteria and guarantee methodological traceability, according to the PRISMA 2020 framework [32]. Initially, 821 records were identified following the execution of the search string across three selected databases: Web of Science (97

records), Scopus (218 records), and IEEE Xplore (506 records).

Subsequently, 145 duplicate records were removed, leaving 676 articles. The initial screening phase was performed based on titles and abstracts. This step was performed by two independent reviewers who applied the previously established inclusion and exclusion criteria. Discrepancies were resolved through discussion and consensus.

Following this review, 630 studies were excluded for not meeting thematic, contextual, or methodological requirements (e.g., studies not situated in higher education, lacking predictive models, or without outcomes related to student success). Ultimately, 46 studies were selected for the final qualitative synthesis.

This procedure is visually summarized in the PRISMA flow diagram (Fig. 1), which was developed according to the PRISMA 2020 report-

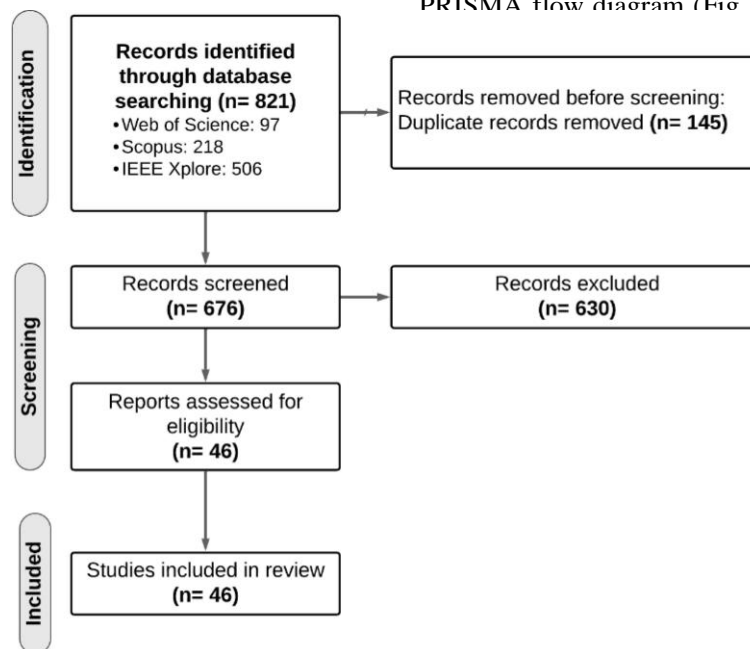


Fig. 1. PRISMA Flow Diagram. Source: Authors' elaboration.

2.5 Methodological Quality Assessment

This review did not apply a formal methodological quality assessment tool (such as CASP, JBI, or MMAT) because the primary objective was to synthesize the technical and pedagogical approaches employed in the use of artificial intelligence in higher education. This requires the analysis of studies with a high degree of heterogeneity in their design, methods, and objectives.

Nevertheless, stringent inclusion criteria were established during the screening phase to ensure minimum quality standards. This limited the corpus to empirical, peer-reviewed studies published in indexed journals that reported outcomes applicable to student success. This strategy is consistent with exploratory and thematic systematic reviews, which aim to map the state of the art rather than compare quantitative effects, as recommended by previous studies [33, 34].

2.6 Data Extraction and Coding

Data extraction was conducted using a structured matrix that included key variables across three levels: (i) general study characteristics (author, year, country, publication type); (ii) technical dimensions (predictive model used, algorithm, reported accuracy, type of chatbot or conversational AI implemented), and (iii) educational outcomes (measured indicators of student success, target population, and institutional context).

A mixed coding system was employed to ensure traceability. In the first stage, the full texts of the 46 selected studies were open coded to identify emerging concepts and relevant thematic patterns. This was followed by axial coding, which aimed to

organize the identified categories around the study's research questions and conceptual frameworks.

Coding was performed independently by two reviewers, and any discrepancies were resolved through consensus.

2.7 Data Analysis

The data analysis followed a qualitative thematic approach, which enabled the identification of patterns, recurrences, and tensions regarding the use of predictive models and chatbots in higher education. This analysis adhered to a mixed inductive–deductive logic: on the one hand, the research questions guided the organization of the main dimensions; on the other hand, emergent categories were allowed to surface, reflecting unforeseen aspects such as ethical tensions, algorithmic bias, or institutional constraints.

The units of analysis were textual excerpts coded during the review of the studies and grouped into three analytical axes: (i) predictive techniques used and their performance, (ii) technical and pedagogical features of the chatbots, and (iii) reported impact on student success. This structure enabled the construction of a critical synthesis aligned with the study objectives and grounded in a coherent empirical foundation.

3. Results

3.1 General Description of the Included Studies

This systematic review analyzed 46 studies published between 2019 and 2024, all of which met the predefined inclusion criteria. Table 3 summarizes the 46 studies included in the analysis.

Table 3. Summary of the 46 selected articles

Article	Research Focus	Key Findings
(36)	Exploration of the impact of AI on the transformation of traditional classrooms into virtual environments, with emphasis on personalized learning and administrative efficiency.	AI enhances personalization, feedback, and accessibility; it fosters student-centered teaching; however, it raises ethical and equity concerns and highlights the need for continuous teacher training.
(37)	Development of a university chatbot using LLMs to answer questions about the student handbook.	The prototype improved the informational experience, understood questions even in Filipino, and reduced administrative workload. Some errors persisted. Users appreciated the natural interaction and suggested broader implementation.
(38)	Evaluation of the use of LLMs (ChatGPT/Copilot) to solve physics problems and promote active learning.	Although LLMs frequently made mistakes, the correction process fostered problem-solving skills. 84% of students improved their use of AI, and 76% reported enhanced conceptual understanding. The study emphasized the need for better prompt engineering and teacher supervision.
(39)	Design, development, and evaluation of a bilingual AI-powered chatbot for academic advising in higher education.	The AVA chatbot provided personalized, 24/7 academic advising. It was perceived as useful and easy to use, supporting student retention, equitable access to information, and needs analysis through usage logs.
(40)	Implementation of a neural network-based chatbot to answer frequently asked questions in university settings.	The chatbot achieved 99.75% accuracy and demonstrated high capacity for intent classification and accurate response generation. Its potential to reduce administrative burden and enhance user experience in educational institutions was highlighted.

Table 3. (Continued)

Article	Research Focus	Key Findings
(41)	Exploration of the use of ChatGPT to generate teacher feedback using emojis and improve student engagement.	The use of emojis in feedback increased motivation, enhanced emotional perception, and fostered a positive attitude toward learning. 77% of participants found their use appropriate, and improvements in retention and engagement were observed.
(42)	Evaluation of ChatGPT’s performance as a support tool (or potential risk) in nuclear medicine education, particularly in written assessments and exams.	ChatGPT performed poorly on calculation questions (24–39%) and written tasks (30–49%), especially in complex, domain-specific topics. It showed some value in introductory content and as a linguistic accessibility tool, but its use requires caution due to hallucinations, lack of references, and academic integrity risks.
(23)	Integration of ChatGPT with active learning methodologies and learning analytics to enhance engagement and reduce anxiety in higher education.	The gamified class using ChatGPT received the highest ratings in terms of engagement and perceived learning. Although the traditional class yielded better objective scores, the classroom experience was more positive with AI. Physiological analytics confirmed higher engagement in the ChatGPT-assisted gamified class.
(43)	Rethinking university assessment methods in response to the emergence of conversational AI, promoting authentic evaluations that foster critical thinking and soft skills.	The critical inclusion of AI in assignments encouraged reflection and responsible use. Students were required to evaluate AI outputs and justify their decisions. The study proposes creating ethical guidelines through collaborative spaces and shifting toward authentic assessments focused on skills and processes rather than outcomes.
(44)	Development of an unsupervised clustering model to identify dropout risk levels using chatbots and data mining algorithms.	The HDBSCAN algorithm proved the most robust, identifying five levels of dropout risk with high accuracy (F-measure: 90.9%, Purity: 94.5%). The study demonstrates the potential of AI-based models for early academic and emotional support interventions.
(45)	Implementation of an academic chatbot for early intervention with at-risk students, based on predictions of academic performance.	The chatbot, triggered by predictive models of attendance and assessments, reduced teaching workload and improved academic support. The prediction model achieved an F1-score of 0.75. Notable features included automated actions based on absence or poor performance and escalation to human intervention.
(46)	Design of a chatbot based on LLaMA 2 for comprehensive support on university websites and prediction of admission cut-off scores.	The chatbot improved user experience on university websites and automated queries related to admissions, scholarships, and services. Regression models achieved high accuracy ($R^2 \approx 0.97$ with XGBoost) in predicting cut-off scores.
(46)	Design of an AI-powered chatbot to improve service on university websites and predict admission cut-off scores.	The chatbot provided contextual responses regarding admissions and student services. Regression models achieved high precision ($R^2 \approx 0.97$ using XGBoost) for cut-off score prediction. The tool enhances user experience and supports institutional decision-making through data-driven insights.
(47)	Application of a chatbot based on Cognitive Behavioral Therapy (CBT) techniques to diagnose and mitigate stress and anxiety in university students.	The chatbot obtained a SUS score of 82.13, exceeding the average for digital health apps. It reduced anxiety and stress levels according to GAD-7 and PSS-14. Its user-centered design, accessibility, and personalization make it a promising tool for student mental well-being.
(48)	Evaluation of the impact of generative chatbots in university teaching and proposal of a theoretical framework for their integration in blended learning.	Identified benefits include personalized support, instructional automation, and increased engagement. The proposed framework facilitates chatbot integration across all course phases, enhancing educational effectiveness. The study underscores the need for ethical guidelines and ongoing impact assessment.
(49)	Proposal of a conceptual AI chatbot framework to improve communication and retention in distance education institutions.	The chatbot enables 24/7 automated responses, improves information access, and reduces dropout rates. Its effectiveness lies in centralizing support and offering personalized responses through NLP and intent classification.
(50)	Integration of intelligent technologies (AI, sensors, wearables) into educational processes to foster self-regulated learning.	The early recognition system identified at-risk students with 75% accuracy in Mathematics and up to 100% in Management. Personalized AI enhanced student engagement, prevented academic failure, and enabled timely interventions through sensors and learning analytics.
(51)	Development of a personalized chatbot for international students based on GPT-3.5-turbo and RAG.	The chatbot outperformed the standard GPT-3.5 model in accuracy, relevance, and fidelity (F1: 0.63 vs. 0.27). It provided real, contextual, and ethical support in areas such as cultural adaptation, mental health, and academic procedures, showing high potential for supporting international students.
(52)	Impact of AI on the educational experience of international students: personalization, chatbots, and analytics.	AI can enhance learning efficiency and provide personalized support, but must be used with attention to privacy risks, cultural biases, and ethical concerns. Chatbots, automatic translators, and writing tools can aid academic adaptation.

Table 3. (Continued)

Article	Research Focus	Key Findings
(53)	Relationship between first-year students' AI competencies and their intended and actual use of AI tools.	Attitude toward AI was the strongest predictor of intended use of tools. Perceived benefits predicted collaborative AI use. Actual use was influenced less by technical knowledge or skills and more by students' interest and curiosity.
(54)	Evaluation of an adaptive system using eye-tracking and ChatGPT-generated summaries to improve comprehension.	The experimental group showed greater comprehension, engagement, and confidence. The model detected real-time attention levels and delivered personalized summaries. Changes in reading patterns demonstrated improved cognitive processing and reduced visual load.
(21)	Comparison of AI model performance versus master's students in a clinical chemistry exam.	ChatGPT-4 significantly outperformed both human students and other AI models in knowledge and comprehension questions. However, it showed weaknesses in higher-order tasks, raising the need to reconsider assessment methods in higher education.
(8)	Evaluation of the impact of a deep learning-based educational platform for personalized learning.	Students using the personalized platform improved by 25% in grades, engagement, and satisfaction. Regression analysis revealed a strong correlation between platform usage and academic performance. Qualitative analysis identified improvements in student comprehension and experience.
(55)	Development and implementation of a chatbot on an institutional web portal to enhance student interaction.	The chatbot provides instant and personalized responses on admissions, courses, financial aid, and more. Its use optimizes administrative processes and improves the student experience in real time. Continuous positive impact is projected, with iterative improvements based on user feedback.
(56)	Evaluation of ChatGPT's impact on dialogic teaching compared to human instructors in a technical course.	ChatGPT was effective in facilitating basic knowledge acquisition (retention), but not in transfer (creative application). EEG data showed higher cognitive activity with ChatGPT, yet students preferred the human instructor for emotional guidance and clarification of doubts.
(57)	Review of the current state and future perspectives of AI use in higher education.	AI optimizes administrative processes, personalizes learning, improves operational efficiency, and enables predictive analytics. Although it holds promise for transforming education, ethical, infrastructural, and teacher training challenges remain.
(58)	Development of a predictive chatbot to support university students' mental health.	Random Forest achieved 82.5% accuracy, outperforming Naive Bayes. The chatbot ("Ampera-Bot") can detect signs of depression, anxiety, or stress and suggest interventions. It demonstrates potential for personalized emotional support and early prevention of mental health issues.
(59)	Implementation of a chatbot using clustering to support low-performing students.	The K-means model identified 7 student clusters based on academic difficulties. The chatbot adjusts the level of intervention according to the group (more support for high-risk students). Accuracy reached 93.5% with an AUC of 0.88, demonstrating that data-driven personalization improves academic support.
(60)	Analysis of the impact, benefits, and challenges of using AI chatbots in university student services.	Chatbots enhance personalized attention, reduce administrative workload, and strengthen student engagement. Ethical and technical challenges such as data privacy and personalization in multilingual contexts were identified.
(61)	Creation of a persona-based conversational system to enhance student engagement in higher education.	Eight student profiles were generated based on participation and performance. Segmentation enables personalized chatbot interaction, improving motivation and engagement. A future evaluation of the prototype using SEFM and a functional chatbot is planned.
(62)	Analysis of behavioral and psychological factors affecting academic performance and proposal of AI-based solutions.	Key factors such as anxiety, isolation, and poor time management were identified as impacting learning. An AI model was proposed to predict academic performance and a chatbot to reduce stress and improve student focus.
(63)	Proposal of a proactive chatbot framework to support students on academic and psychosocial issues.	The chatbot offers personalized, multimodal, and contextualized assistance. It improves student-assistant interaction, recommends critical factors based on profile, and allows feedback to improve responses.
(28)	Exploration of the impact of generative artificial intelligence, especially ChatGPT, on improving teaching and assessment in higher education.	Prompt engineering is a key skill for educators; AI can improve feedback, personalize content, and effectively redesign assessments.
(64)	Development of a system to identify key phrases from lecture videos for feedback in MOOCs.	The hybrid GPT method with BERT vectors yielded better precision. Students positively valued visual and auditory feedback with key phrases.

Table 3. (Continued)

Article	Research Focus	Key Findings
(65)	Systematic review on student-centered adaptive instruction and its effectiveness.	Student motivation, prior experience with digital tools, and instructional design are key factors for the success of adaptive instruction using AI technologies.
(66)	Implementation of AI-based tools to support students and faculty in the creation and evaluation of educational content in Moodle.	Integration of chatbots such as ChatGPT-4 and automation of materials using PowerShell scripts significantly reduced content creation time; adaptive feedback enhanced the learning experience.
(67)	Exploration of the transformative impact of AI on pedagogy and educational administration.	AI personalizes learning via AR/VR, improves administrative efficiency, raises ethical concerns (privacy, bias), and requires ongoing faculty development.
(68)	Evaluation of the impact of AI tools on student success.	Chatbots and writing tools are widely used; three student profiles were identified based on usage/interest; the need for teacher support and ethical training was emphasized.
(69)	Systematic review of AI-LMS integration and its contribution to educational sustainability and quality.	AI-LMS integration improves student engagement, personalized learning, and efficiency; challenges include algorithmic bias, data privacy, and faculty training.
(70)	Analysis of AI tool usage among university students.	High adoption of ChatGPT, Grammarly, and Canva; three student clusters were identified based on usage/interest; ethical and strategic AI integration is recommended.
(71)	Exploration of the transformative potential of AI in higher education.	AI enhances learning through adaptive systems, virtual assistants, administrative automation, and research platforms, but presents ethical challenges related to privacy, equity, and job displacement.
(15)	Evaluation of a practical case of ChatGPT integration in Tunisian higher education.	85% of students used the NAJEH chatbot (based on ChatGPT) daily. Its positive impact was noted in personalized learning, teaching efficiency, and critical skill development.
(72)	Analysis of factors influencing ChatGPT acceptance using the extended UTAUT2 model.	Acceptance of ChatGPT is influenced by performance expectancy, perceived effort, and knowledge-sharing practices.
(73)	Proposal of educational solutions through machine learning to address structural challenges in African higher education.	Personalized learning, predictive analytics, and virtual assistants can improve access, reduce dropout, and counter bias in assessment. A call is made for a locally grounded, digitized, and equitable educational system.
(74)	Development of a personalized recommendation system for international students based on ANN and collaborative filtering.	The system achieved 91.02% accuracy. It outperforms ChatGPT by considering complete student profiles and providing personalized admission rates. It is recommended for its robustness, personalization, and continuous improvement through feedback.
(75)	Proposal of a generative AI chatbot to assess and intervene in self-regulated learning (SRL) skills	Friendly chatbot conversation is proposed as a way to overcome the limitations of traditional surveys and improve SRL interventions. It is expected to reduce dropout through conversational interaction in the style of a mentor or virtual friend.

For each study, the research focus and key findings were detailed, providing an overview of the evidence.

The annual publication output showed a consistent increase throughout the analysis period, with a particularly notable increase over the last two years. Only one study was published in 2019, 2020, or 2021. In 2022, the number rose to two publications, and ten studies were identified in 2023. The peak in scientific production occurred in 2024, with 31 publications, representing 67.4% of the total publications (Fig. 2).

This accelerated growth is reflected in an average annual growth rate of 98.73%, highlighting the increasing interest of the scientific community in the use of predictive models and artificial intelligence chatbots in higher education. The average age of the documents was 1.57 years, confirming the recency of the analyzed literature, with an average of 9.52 citations per document.

From an authorship perspective, 176 authors

contributed to the included studies, with an average of four co-authors per study. International collaboration was recorded in 23.91% of the studies, reinforcing the global nature of the research field. Only three publications were single authored.

In terms of geographical distribution, the bibliometric analysis revealed that India led scientific output ($n = 17$), followed by Indonesia ($n = 11$), the United Kingdom and Peru (each with $n = 7$), and Germany ($n = 5$), among other countries (Fig. 3). This distribution reflects a diverse international landscape, although it is concentrated in regions with high capacity for technological and educational innovations.

3.2 Machine Learning Techniques Used for Prediction

The reviewed studies reveal the growing and diverse applications of machine learning techniques to predict dropout risk, academic performance, and other indicators related to student's success.

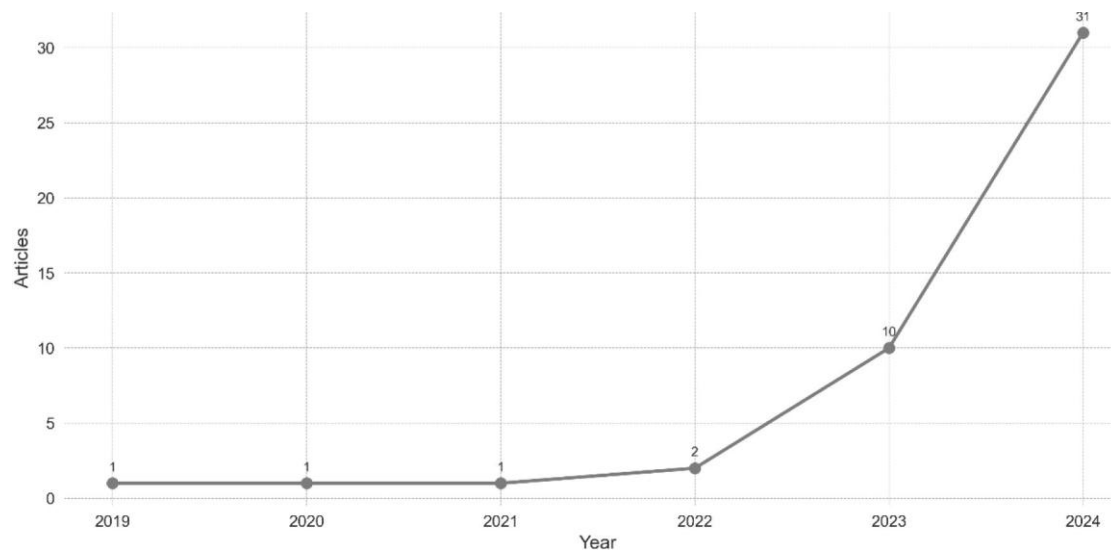


Fig. 2. Annual Scientific Production. Source: Authors' elaboration using the Bibliometrix and Biblioshiny packages in R.



Fig. 3. Country's Scientific Production Map. Source: Authors' elaboration using Bibliometrix and Biblioshiny packages in R.

This review identified four main families of algorithms: artificial neural networks (ANN), decision trees and ensemble methods, support vector machines (SVM), and probabilistic models. Additionally, some studies have incorporated hybrid or complementary approaches, such as natural language processing (NLP) and unsupervised techniques such as clustering.

3.2.1 Artificial Neural Networks

Artificial neural networks (ANNs) have been widely employed in the analyzed studies, particularly for modeling complex relationships and personalizing learning pathways. In [50], neural models applied to Moodle platform data achieved 100% accuracy in predicting performance in sub-

jects such as knowledge management. Similarly, in [40], a chatbot was developed using a multilayer neural network based on TensorFlow, which achieved outstanding performance ($F1 = 99.75\%$). In [74], a collaborative neural network outperformed other supervised models in predicting admissions with 91% accuracy.

Additionally, [8] CNN and RNN architectures were implemented to adapt the content in real time, resulting in a 25% improvement in student performance and engagement. The Transformer architecture underpinning large language models (LLMs), such as ChatGPT, has been frequently cited in studies [15, 37, 63], highlighting its central role in natural language processing.

Other studies [47, 51, 54] have also reported the

1 use of advanced neural architectures (e.g., Bi-
2 LSTM and RAG) for emotional analysis, anxiety
3 diagnosis, and content personalization. Collec-
4 tively, these studies demonstrate the growing pro-
5 minence of ANNs and deep learning in intelligent
6 educational systems, whether using traditional
7 supervised models or state-of-the-art conversa-
8 tional large LLMs.

9 3.2.2 Decision Trees and Ensemble Algorithms

10 Decision tree-based algorithms and their ensemble
11 variants, such as random forest classifiers (RFC),
12 have been widely used in the educational domain.
13 In [58], the RFC achieved an accuracy of 82.5% in
14 predicting the symptoms of depression and anxiety,
15 outperforming the Bayesian model owing to its
16 ability to combine multiple trees through majority
17 voting and reduce overfitting.

18 [76] applied decision tree regression, random
19 forest regression, and gradient boosting regression
20 to predict the admission cut-off scores. In [62], both
21 decision trees and random forests were used in
22 predictive models, emphasizing that their perfor-
23 mance depends on the data quality and quantity.
24 [74] compared decision trees and random forests
25 with an ensemble neural network, while [45]
26 included the random tree algorithm to predict
27 student grades and cited a previous study by [77],
28 who evaluated the use of the C4.5 decision tree in
29 academic assessment contexts.

30 These studies underscore the versatility and
31 robustness of tree-based algorithms, particularly
32 for classification, regression, and personalized
33 advising tasks.

34 3.2.3 Support Vector Machines (SVM)

35 Support Vector Machines (SVMs) have been used
36 in various studies related to prediction and classifi-
37 cation in educational contexts. In [50], an SVM with
38 a radial kernel was employed to classify students at
39 academic risk based on LMS interaction data,
40 highlighting its usefulness for structured datasets.
41 In [58], the SVM outperformed the Random Forest
42 in predicting anxiety, whereas the latter was more
43 effective in detecting depression. [76] applied Sup-
44 port Vector Regression (SVR) to predict admission
45 cut-off scores, leveraging its capacity to model time-
46 series data. In [62], SVM was evaluated alongside
47 other algorithms, and the results showed that its
48 performance depended on data quality and volume.
49 Additionally, [74] SVM was used as a benchmark
50 against collaborative neural networks, and [61] its
51 prior use in recognizing complex patterns was cited.
52 These studies underscore the versatility of SVM
53 and its variants in both classification and regression
54 tasks, although their effectiveness varies depending
55 on the context and alternative algorithms used.

56 3.2.4 Probabilistic Models (Naive Bayes)

57 The Multinomial Naive Bayes (MNB) algorithm
has been widely applied in text classification and
intent recognition in chatbots owing to its simpli-
city and computational efficiency. [49] proposed its
use as a primary classifier in conversational systems
owing to its high applicability and precision in low-
cost computing environments, and [49] used it to
detect at-risk students through a chatbot based on
the DASS-21 inventory, although it yielded lower
accuracy (66%) than the Random Forest (82.5%).
[62] also used Naive Bayes as a comparative refer-
ence, outperforming algorithms such as k-NN in
terms of accuracy. Collectively, these studies high-
light MNB as a useful option when speed and
simplicity are prioritized over predictive precision.

17 3.2.5 Other Approaches: Clustering and Hybrid 18 Models

19 Recent studies [70] have employed K-means clus-
20 tering to segment students based on their use of and
21 interest in AI tools (chatbots, grammar checkers,
22 code generators), enabling personalized interven-
23 tions without direct predictive goals. Similarly, [59]
24 integrated clustering and natural language proces-
25 sing (NLP) to automate differentiated interventions
26 with a predictive focus on academic performance.
27 Other studies, such as [61], used density-based
28 clustering models that combine behavioral or emo-
29 tional data with clustering and NLP to personalize
30 educational strategies with or without predictive
31 purposes.

32 3.3 Identified Limitations

33 Despite the promising nature of the quantitative
34 results, numerous reviewed studies highlight the
35 common limitations that affect the implementation
36 and validity of AI-based solutions in higher-educa-
37 tion settings. One of the most frequently reported
38 constraints is the lack of interpretability in complex
39 models, such as neural networks, [74], which hin-
40 ders their acceptance in pedagogical contexts.
41 Additionally, [37, 40] chatbots often suffer from
42 issues related to accuracy, knowledge updating, and
43 conversational continuity, which compromise the
44 quality of the interaction.

45 Other studies [38, 42] have warned about super-
46 ficial responses, content inaccuracies, and limita-
47 tions in higher-order tasks, raising concerns
48 regarding the cognitive depth of the responses.
49 Methodological challenges have also been identi-
50 fied, such as the lack of experimental control or
51 cross-validation, as reported by [23], along with
52 generalization issues when models are applied to
53 populations different from those used in the origi-
54 nal training datasets [39, 45].

1 Algorithmic fairness remains a concern: [51, 74] it
2 underscores the risk of bias due to data imbalances,
3 while [60] highlights the lack of algorithmic trans-
4 parency and the cultural-linguistic impact of chat-
5 bots. At both ethical and practical levels, studies
6 such as [57, 72] emphasize the need for clear policies
7 on privacy, data protection, and responsible use, as
8 well as the need to ensure technical sustainability
9 and equitable accessibility.

10 Finally, the limited quality of the outputs gener-
11 ated by language models, along with their varying
12 performance across academic disciplines, has been
13 noted in previous studies [21, 70]. These limitations
14 underscore the importance of critically, contex-
15 tually, and ethically integrating AI into educational
16 environments.

17 4. Discussion

18 4.1 Comparison Among the Reviewed Studies

19 The analysis of the 46 selected studies revealed
20 technological and pedagogical convergence
21 beyond the isolated use of AI tools. The findings
22 suggest the emergence of an AI-driven early inter-
23 vention cycle in higher education, which is a con-
24 ceptual framework that integrates the detection
25 capabilities of predictive models with the persona-
26 lized responses of conversational agents. This cycle
27 consists of three interconnected phases: (1) Predic-
28 tive Detection, (2) Conversational Intervention,
29 and (3) Refinement and Feedback. The results of
30 this review will be discussed in light of this con-
31 ceptual framework, analyzing its practical and
32 pedagogical implications and future research direc-
33 tions derived from it.

34 From a predictive perspective, studies such as
35 [12–14] highlight the effectiveness of hybrid models
36 and neural networks in anticipating student drop-
37 out, achieving accuracy rates of approximately
38 96%. These investigations rely on large volumes of
39 historical data (grades, LMS participation, and
40 demographic information) to train algorithms
41 such as Random Forest, SVM, deep neural net-
42 works, and clustering techniques, consolidating a
43 technically robust approach. However, this
44 approach is subject to criticism regarding its
45 explainability and transparency [11, 25].

46 Conversely, research on chatbots has demon-
47 strated significant functional and pedagogical
48 expansion. Studies [15, 37] have explored the poten-
49 tial of language model-powered chatbots, such as
50 ChatGPT, to provide virtual tutoring, emotional
51 support, and 24/7 administrative assistance. Others
52 [40, 47] have proposed frameworks based on NLP
53 and deep learning that achieve outstanding levels of
54 conversational performance ($F1 > 99\%$). At the
55 pedagogical level, there is increasing alignment
56

1 with adaptive and constructivist learning theories
2 [17–19], although limitations remain in terms of
3 interaction quality, cognitive depth, and potential
4 displacement of human support [28, 30].

5 In contrast to reviews that exclusively focus on
6 the technical dimensions or functional impact of
7 chatbots, this study proposes an integrated perspec-
8 tive. While studies such as [16, 22] offer a functional
9 taxonomy of chatbots and [52] emphasize their role
10 in supporting international students, our combined
11 review enables a comprehensive understanding of
12 the full intervention cycle, from early detection (via
13 predictive models) to personalized responses (via
14 conversational AI).

15 In summary, this systematic review reveals the
16 progressive maturation of the field toward syner-
17 gistic solutions, where predictive models and con-
18 versational agents do not operate as isolated
19 technologies but as integrated components of a
20 personalized, ethical, and context-sensitive student
21 support ecosystem.

22 4.2 Reflection on Practical and Pedagogical 23 Implications

24 The findings of this systematic review not only
25 highlight technological advancements in the educa-
26 tional field but also invite critical reflection on the
27 practical and pedagogical implications of imple-
28 menting machine learning models and chatbots in
29 higher education.

30 From a practical standpoint, the adoption of
31 predictive models within institutional contexts
32 opens new opportunities for the design of more
33 accurate and efficient early warning systems. These
34 models enable the identification of academic risk
35 patterns in advance, allowing for personalized
36 interventions that, if properly implemented, could
37 significantly reduce dropout rates and improve
38 student retention [12, 14]. However, their usefulness
39 depends directly on the quality and representative-
40 ness of the data, as well as the institutional capacity
41 to translate predictions into concrete, ethical, and
42 sustainable actions [6, 11].

43 The practical implementation of chatbots has
44 demonstrated clear benefits in automating routine
45 tasks, ensuring the 24/7 availability of academic
46 support, and providing continuous guidance to
47 students at various stages of their academic jour-
48 neys [40, 48]. Particularly in high-enrollment sce-
49 narios with limited personalized attention, these
50 tools can ease administrative and instructional
51 burdens, enhancing the user experience through
52 immediate and tailored responses to student
53 queries. However, their effectiveness depends on
54 semantic accuracy, up-to-date knowledge, and the
55 ability to respond to student needs in context.

56 From a pedagogical perspective, both predictive
57

1 models and conversational agents must be under- 1
 2 stood not only as technological tools but also as 2
 3 actors within the educational ecosystem. Their 3
 4 effective integration requires alignment with frame- 4
 5 works such as adaptive learning, scaffolding theory, 5
 6 and student-centered pedagogy [18, 19]. A well- 6
 7 designed chatbot can function as a virtual tutor, 7
 8 fostering autonomy and formative feedback, 8
 9 whereas a predictive system can enable instructors 9
 10 to anticipate the specific needs of their students and 10
 11 adjust their teaching strategies accordingly. 11

12 Nevertheless, these technologies also present 12
 13 pedagogical challenges, such as the risk of students 13
 14 becoming overly reliant on automated responses, 14
 15 the depersonalization of the learning process, and 15
 16 the danger of reducing educational intervention in a 16
 17 technical process that is disconnected from human 17
 18 connection. As noted by [28, 30], instructors' empa- 18
 19 thetic presence remains an irreplaceable component 19
 20 in fostering belonging, motivation, and critical 20
 21 thinking. 21

22 Consequently, the practical and pedagogical 22
 23 implications of these technologies must be 23
 24 approached using the logic of complementarity. 24
 25 Institutions must not only invest in intelligent 25
 26 tools but also develop pedagogical, ethical, and 26
 27 training frameworks to ensure their responsible, 27
 28 inclusive, and genuinely learning-centered use. 28
 29

30 *4.3 Tensions, Gaps, and Future Research* 31 *Opportunities*

32 Despite significant advances in the use of predictive 32
 33 models and chatbots in higher education, the 33
 34 reviewed studies reveal persistent tensions and 34
 35 critical gaps that limit their effective and sustainable 35
 36 impact on education. 36

37 The first tension identified is the trade-off 37
 38 between accuracy and interpretability of the 38
 39 model. Although models such as deep neural net- 39
 40 works, random forests, and hybrid algorithms have 40
 41 achieved remarkable levels of accuracy [12, 14], 41
 42 their application in educational contexts raises 42
 43 ethical and pedagogical challenges. As noted in 43
 44 [11], the lack of transparency in the decision- 44
 45 making criteria of such models hinders their accep- 45
 46 tance by instructors and non-technical staff, gen- 46
 47 erating institutional resistance and limiting their 47
 48 real-world applicability in learning environments. 48

49 Second, a lack of deep pedagogical integration 49
 50 persisted in the data. Although some studies high- 50
 51 light the alignment of chatbots with frameworks 51
 52 such as adaptive learning or cognitive load theory 52
 53 [18], others [16, 22] indicate that most implementa- 53
 54 tions focus on technical functionality (e.g., answer- 54
 55 ing questions and automating processes) without a 55
 56 genuine articulation of educational goals or criteria 56
 57 for deep learning assessment. 57

A further gap is geographic and cultural; most 1
 studies are conducted in English-speaking or 2
 Southeast Asian contexts, with limited representa- 3
 tion from Latin American, African, and rural 4
 institutions and contexts. This limitation [51] 5
 restricts the generalizability of the findings and 6
 underscores the need for localized research that 7
 accounts for cultural, linguistic, and technological 8
 diversity. 9

10 From a functional standpoint, another major gap 10
 11 is the lack of longitudinal and multivariate evalua- 11
 12 tions. Most reviewed studies reported immediate or 12
 13 short-term effects on variables such as retention or 13
 14 academic performance, but few examined sustained 14
 15 impacts over time or integrated psychoeducational 15
 16 variables such as self-efficacy, academic anxiety, or 16
 17 sense of belonging. [54] raised this concern when 17
 18 exploring how chatbots may mediate attention and 18
 19 cognitive load but without conclusive longitudinal 19
 20 data to support their claims. 20

21 Finally, there is a growing opportunity to explore 21
 22 integrated intervention models that combine pre- 22
 23 dictive capacity and pedagogical adaptability. Stu- 23
 24 dies [59] have shown that the combined use of 24
 25 clustering and NLP allows for more effective per- 25
 26 sonalized interventions; however, these remain iso- 26
 27 lated cases. This opens a promising research 27
 28 avenue: the development of educational AI ecosys- 28
 29 tems that not only detect risks but also execute 29
 30 interventions based on personalized, ethical, and 30
 31 culturally relevant learning models. 31

32 In summary, the current challenges are not 32
 33 merely technical but also deeply educational and 33
 34 sociocultural. The future of this field depends on its 34
 35 ability to integrate artificial intelligence with sound 35
 36 pedagogical principles, inclusive strategies, and an 36
 37 ethical vision, oriented toward human develop- 37
 38 ment. 38
 39

40 **5. Conclusion**

41 This systematic review provides an integrative per- 41
 42 spective on the use of two artificial intelligence 42
 43 applications in higher education: machine learn- 43
 44 ing-based predictive models and educational 44
 45 chatbots as complementary tools for early interven- 45
 46 tions. Based on an analysis of 46 studies published 46
 47 between 2019 and 2024, a growing trend was 47
 48 observed in the use of these technologies to antici- 48
 49 pate dropout risk, personalize student support, and 49
 50 automate academic and administrative support 50
 51 processes [9, 10, 37]. 51
 52

53 Based on the research questions posed, the fol- 53
 54 lowing conclusions can be drawn: 54
 55

- 56 • The most frequently used machine learning tech- 56
 57 niques for predicting dropout risk include neural 57

networks, decision tree algorithms, support vector machines, and hybrid models, with several studies reporting accuracy rates above 90% [12–14].

- Educational chatbots have made notable technical and pedagogical progress. Many leverage natural language processing and architectures such as Transformer or Bi-LSTM, enabling them to generate contextualized responses and promote personalized learning [15, 54, 63].
- While the impact of these technologies is moderate, it is positive across key indicators such as academic performance, motivation, and retention. Tools such as NAJEH and assistants [40, 47] demonstrated perceived improvements in accessibility, availability, and student support.

It is essential to emphasize that this review does not provide a comprehensive overview of artificial intelligence in education. Rather, it focuses exclusively on applications related to academic risk prediction and chatbot-based intervention. This

narrower scope allows for a deeper analysis of a specific segment, avoiding generalizations about the broader state of educational AI.

From a practical perspective, the results may guide higher-education institutions and policy-makers toward the ethical, pedagogically coherent, and technically feasible implementation of these tools. Predictive models enable the deployment of efficient early warning systems, and well-integrated chatbots can enhance institutional interaction, reduce instructional workload, and support student decision-making [23, 24].

Taken together, this study underscores the need to move toward integrated intervention models in which AI systems not only identify at-risk students but also trigger formative responses aligned with principles such as adaptive learning, equity, and holistic development. The articulation of predictive analytics and conversational support represents a strategic opportunity to build more inclusive, efficient, and human-centered educational environments.

References

1. M. Hanson, *College Dropout Rate*, EducationData.org, <https://educationdata.org/college-dropout-rates>, Accessed 23 March 2025.
2. A. Arias, M. Linares-Va'squez and N. R. He'ndez-Puerto, The article title, *Journal of Latino Education*, **23**(2), pp. 612–627, 2024.
3. L. E. Ávila Granda, F. Cepeda Yautibug and R. Aucancela Copa, Dropout in Higher Education in Ecuador, Causes and Consequences, *Ciencia Latina Revista Cient'ifica Multidisciplinar*, **8**(3), pp. 11475–11490, 2024.
4. P. Perchinunno, M. Bilancia and D. Vitale, A Statistical Analysis of Factors Affecting Higher Education Dropouts, *Social Indicators Research*, **156**(2–3), pp. 341–362, 2021.
5. J. C. de la Cruz-Campos, J. J. Victoria-Maldonado, J. A. Mart'inez-Domingo and M. N. Campos-Soto, Causes of academic dropout in higher education in Andalusia and proposals for its prevention at university: A systematic review, *Frontiers in Education*, **8**, pp. 1–15, 2023.
6. A. Almalawi, B. Soh, A. Li and H. Samra, Predictive Models for Educational Purposes: A Systematic Review, *Big Data and Cognitive Computing*, **8**(12), p. 187, 2024.
7. E. Alhazmi and A. Sheneamer, Early Predicting of Students Performance in Higher Education, *IEEE Access*, **11**, pp. 27579–27589, 2023.
8. F. Naseer, M. N. Khan, M. Tahir, A. Addas and S. M. H. Aejaz, Integrating deep learning techniques for personalized learning pathways in higher education, *Heliyon*, **10**(11), p. e32628, 2024.
9. B. Albreiki, T. Habuza and N. Zaki, Extracting topological features to identify at-risk students using machine learning and graph convolutional network models, *International Journal of Educational Technology in Higher Education*, **20**(1), pp. 1–22, 2023.
10. H. Kaur, T. Kaur and R. Garg, A Prediction Model for Online Student Academic Performance Using Machine Learning, *Informatica*, **47**(1), pp. 97–108, 2023.
11. S. Chen and Y. Ding, A Machine Learning Approach to Predicting Academic Performance in Pennsylvania's Schools, *Social Sciences*, **12**(3), p. 118, 2023.
12. S. Kim, E. Choi, Y. K. Jun and S. Lee, Student Dropout Prediction for University with High Precision and Recall, *Applied Sciences*, **13**(10), p. 6275, 2023.
13. S. Mustofa, Y. R. Emon, S. Bin Mamun, S. A. Akhy and M. T. Ahad, A novel AI-driven model for student dropout risk analysis with explainable AI insights, *Computers and Education: Artificial Intelligence*, **8**, p. 100352, 2025.
14. A. M. Rabelo and L. E. Za'rate, A model for predicting dropout of higher education students, *Data Science and Management*, **8**(1), pp. 72–85, 2025.
15. A. Abid, M. Somai, H. M. Kammoun and I. Kallel, The NAJEH Effect: How ChatGPT is Shaping the Future of Higher Education, *Proceedings of the 21st International Conference on Information Technology Based Higher Education and Training (ITHET)*, Paris, pp. 1–8, 2024.
16. C. W. Okonkwo and A. Ade-Ibijola, Chatbots applications in education: A systematic review, *Computers and Education: Artificial Intelligence*, **2**, p. 100033, 2021.
17. G. Cooper, Cognitive load theory as an aid for instructional design, *Australasian Journal of Educational Technology*, **6**(2), 1990.
18. B. K. Mungai, P. K. Kabeti Omieno, Dr. M. Egezza and P. N. Manyara, AI Chatbots in LMS: A Pedagogical Review of Cognitive, Constructivist, and Adaptive Principles, *Engineering and Technology Journal*, **9**(8), pp. 4709–4715, 2024.
19. J. Sweller, Cognitive load theory and educational technology, *Educational Technology Research and Development*, **68**(1), pp. 1–16, 2020.

- 1 20. G. Ilieva, T. Yankova, S. Klisarova-Belcheva, A. Dimitrov, M. Bratkov and D. Angelov, Effects of Generative Chatbots in Higher Education, *Information*, **14**(9), p. 492, 2023. 1
- 2 21. M. Sallam, K. Al-Salahat, H. Eid, J. Egger and B. Puladi, Human versus Artificial Intelligence: ChatGPT-4 Outperforming Bing, Bard, ChatGPT-3.5 and Humans in Clinical Chemistry Multiple-Choice Questions, *Advances in Medical Education and Practice*, **15**, pp. 857–871, 2024. 2
- 3 22. L. Labadze, M. Grigolia and L. Machaidze, Role of AI chatbots in education: systematic literature review, *International Journal of Educational Technology in Higher Education*, **20**(1), pp. 1–17, 2023. 3
- 4 23. M. Civit, M. J. Escalona, F. Cuadrado and S. Reyes-de-Cozar, Class integration of ChatGPT and learning analytics for higher education, *Expert Systems*, **41**(12), p. e13703, 2024. 4
- 5 24. M. Laun and F. Wolff, Chatbots in education: Hype or help? A meta-analysis, *Learning and Individual Differences*, **119**, p. 102646, 2025. 5
- 6 25. R. Costa-Mendes, F. Cruz-Jesus, T. Oliveira and M. Castelli, Machine Learning Bias in Predicting High School Grades: A Knowledge Perspective, *Emerging Science Journal*, **5**(5), pp. 576–597, 2021. 6
- 7 26. D. Hooshyar and Y. Yang, Neural-symbolic computing: a step toward interpretable AI in education, *Bulletin of the Technical Committee on Learning Technology*, **21**(4), pp. 2–6, 2021. 7
- 8 27. T. Tong and Z. Li, Predicting learning achievement using ensemble learning with result explanation, *PLoS ONE*, **20**(1), p. e0312124, 2025. 8
- 9 28. B. Eager and R. Brunton, Prompting Higher Education Towards AI-Augmented Teaching and Learning Practice, *Journal of University Teaching and Learning Practice*, **20**(5), 2023. 9
- 10 29. B. Kayali, M. Yavuz, S. Balat and M. C. alis˘an, Investigation of student experiences with ChatGPT-supported online learning applications in higher education, *Australasian Journal of Educational Technology*, **39**(5), pp. 20–39, 2023. 10
- 11 30. J. Crawford, K. A. Allen, B. Pani and M. Cowling, When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention, *Studies in Higher Education*, **49**(5), pp. 883–897, 2024. 11
- 12 31. M. A. Kuhail, N. Alturki, J. Thomas and A. K. Alkhalifa, Human vs. AI counseling: College students’ perspectives, *Computers in Human Behavior Reports*, **16**, p. 100534, 2024. 12
- 13 32. M. J. Page, D. Moher, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow et al., PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews, *BMJ*, **372**, 2021. 13
- 14 33. H. Snyder, Literature review as a research methodology: An overview and guidelines, *Journal of Business Research*, **104**, pp. 333–339, 2019. 14
- 15 34. B. A. Kitchenham, Systematic review in software engineering, *ACM Digital Library*, pp. 1–2, 2012. 15
- 16 35. D. Tranfield, D. Denyer and P. Smart, Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review, *British Journal of Management*, **14**(3), pp. 207–222, 2003. 16
- 17 36. F. Nurhasanah, A. S. C. Nugraheni, B. Kusharjanta, R. Ardiansyah, S. Widono and K. Saddhono, A design of virtual classrooms through AI, ML and DL to improve the level of learning, *Proceedings of the 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, pp. 940–945, 2024. 17
- 18 37. J. B. Ilagan and J. R. Ilagan, A prototype of a conversational virtual university support agent powered by a large language model that addresses inquiries about policies in the student handbook, in R. F. C. da C. Goncalves Martinho (ed), *Procedia Computer Science*, **239**, Elsevier, pp. 1124–1131, 2024. 18
- 19 38. V. Robledo-Rella and B. Y. Toh, Artificial intelligence in physics courses to support active learning, *Proceedings of the 10th International Conference on E-Society, e-Learning and e-Technologies (ICSLT)*, pp. 68–75, 2024. 19
- 20 39. F. Torres-Cruz, L. Coyla-Idme, J. C. Juarez-Vargas, R. Singh, M. Upender and D. Kapila, Bilingual Chatbot Powered by Artificial Intelligence for Academic Advice, *Proceedings of the Global Conference on Information Technologies and Communications (GCITC)*, Bangalore, pp. 1–6, 2023. 20
- 21 40. S. A. Salloum, K. Shalan, A. Basiouni, A. Salloum and R. Alfaisal, Building and Evaluating a Chatbot Using a University FAQs Dataset, in A. Basiouni (ed), *Communications in Computer and Information Science*, **2162**, pp. 207–218, 2024. 21
- 22 41. E. Kupershtein, Y. Kumar, A. Manikandan, P. Morreale and J. J. Li, ChatGPT as a Game-Changer for Embedding Emojis in Faculty Feedback, *Proceedings of the 2023 Congress in Computer Science, Computer Engineering, and Applied Computing (CSCE)*, Las Vegas, NV, pp. 1039–1046, 2023. 22
- 23 42. G. Currie and K. Barry, ChatGPT in Nuclear Medicine Education, *Journal of Nuclear Medicine Technology*, **51**(3), pp. 247–254, 2023. 23
- 24 43. D. J. Cranfield, I. M. Venter and J. Mulyata, Conversational Artificial Intelligence: A Catalyst for Rethinking Assessment in Higher Education, in N. A. Obermayer (ed), *Proceedings of the 25th European Conference on Knowledge Management (ECKM)*, Academic Conferences and Publishing International Limited, pp. 1097–1105, 2024. 24
- 25 44. M. A. Valles-Coral, L. Salazar-Ram´irez, R. Injante, E. A. Hernandez-Torres, J. Jua´rez-D´ıaz, J. R. Navarro-Cabrera et al., Density-Based Unsupervised Learning Algorithm to Categorize College Students into Dropout Risk Levels, *Data*, **7**(11), 2022. 25
- 26 45. M. S. Lim, S. B. Ho and I. Chai, Design and Functionality of a University Academic Advisor Chatbot as an Early Intervention to Improve Students’ Academic Performance, in A. R. Alfred and H. H. Iida (eds), *Lecture Notes in Electrical Engineering*, **724**, pp. 167–178, 2021. 26
- 27 46. R. Thamilselvan, P. Natesan, A. Manimaran, S. E. Naveenkumar, J. K. Shanthosh and S. Vigneshwaran, Designing a Llama 2-Powered Chatbot for Enhanced College Website Support, *Proceedings of the 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kamand, p. 1, 2024. 27
- 28 47. G. De La Puente, A. Silva and R. Felix, Development of a chatbot powered by artificial intelligence to diagnose and improve stress and anxiety levels in university students, *Proceedings of the IEEE XXXI International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*, Lima, pp. 1–8, 2024. 28
- 29 48. G. Ilieva, T. Yankova, S. Klisarova-Belcheva, A. Dimitrov, M. Bratkov and D. Angelov, Effects of Generative Chatbots in Higher Education, *Information*, **14**(9), 2023. 29
- 30 49. J. N. Ndunagu, R. G. Jimoh, U. Chidiebere and G. D. Opeoluwa, Enhanced Open and Distance Learning Using an Artificial Intelligence (AI)-Powered Chatbot: a Conceptual Framework, *Proceedings of the 5th Information Technology for Education and Development (ITED)*, Abuja, pp. 1–4, 2022. 30
- 31 31. M. A. Kuhail, N. Alturki, J. Thomas and A. K. Alkhalifa, Human vs. AI counseling: College students’ perspectives, *Computers in Human Behavior Reports*, **16**, p. 100534, 2024. 31
- 32 32. M. J. Page, D. Moher, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow et al., PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews, *BMJ*, **372**, 2021. 32
- 33 33. H. Snyder, Literature review as a research methodology: An overview and guidelines, *Journal of Business Research*, **104**, pp. 333–339, 2019. 33
- 34 34. B. A. Kitchenham, Systematic review in software engineering, *ACM Digital Library*, pp. 1–2, 2012. 34
- 35 35. D. Tranfield, D. Denyer and P. Smart, Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review, *British Journal of Management*, **14**(3), pp. 207–222, 2003. 35
- 36 36. F. Nurhasanah, A. S. C. Nugraheni, B. Kusharjanta, R. Ardiansyah, S. Widono and K. Saddhono, A design of virtual classrooms through AI, ML and DL to improve the level of learning, *Proceedings of the 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, pp. 940–945, 2024. 36
- 37 37. J. B. Ilagan and J. R. Ilagan, A prototype of a conversational virtual university support agent powered by a large language model that addresses inquiries about policies in the student handbook, in R. F. C. da C. Goncalves Martinho (ed), *Procedia Computer Science*, **239**, Elsevier, pp. 1124–1131, 2024. 37
- 38 38. V. Robledo-Rella and B. Y. Toh, Artificial intelligence in physics courses to support active learning, *Proceedings of the 10th International Conference on E-Society, e-Learning and e-Technologies (ICSLT)*, pp. 68–75, 2024. 38
- 39 39. F. Torres-Cruz, L. Coyla-Idme, J. C. Juarez-Vargas, R. Singh, M. Upender and D. Kapila, Bilingual Chatbot Powered by Artificial Intelligence for Academic Advice, *Proceedings of the Global Conference on Information Technologies and Communications (GCITC)*, Bangalore, pp. 1–6, 2023. 39
- 40 40. S. A. Salloum, K. Shalan, A. Basiouni, A. Salloum and R. Alfaisal, Building and Evaluating a Chatbot Using a University FAQs Dataset, in A. Basiouni (ed), *Communications in Computer and Information Science*, **2162**, pp. 207–218, 2024. 40
- 41 41. E. Kupershtein, Y. Kumar, A. Manikandan, P. Morreale and J. J. Li, ChatGPT as a Game-Changer for Embedding Emojis in Faculty Feedback, *Proceedings of the 2023 Congress in Computer Science, Computer Engineering, and Applied Computing (CSCE)*, Las Vegas, NV, pp. 1039–1046, 2023. 41
- 42 42. G. Currie and K. Barry, ChatGPT in Nuclear Medicine Education, *Journal of Nuclear Medicine Technology*, **51**(3), pp. 247–254, 2023. 42
- 43 43. D. J. Cranfield, I. M. Venter and J. Mulyata, Conversational Artificial Intelligence: A Catalyst for Rethinking Assessment in Higher Education, in N. A. Obermayer (ed), *Proceedings of the 25th European Conference on Knowledge Management (ECKM)*, Academic Conferences and Publishing International Limited, pp. 1097–1105, 2024. 43
- 44 44. M. A. Valles-Coral, L. Salazar-Ram´irez, R. Injante, E. A. Hernandez-Torres, J. Jua´rez-D´ıaz, J. R. Navarro-Cabrera et al., Density-Based Unsupervised Learning Algorithm to Categorize College Students into Dropout Risk Levels, *Data*, **7**(11), 2022. 44
- 45 45. M. S. Lim, S. B. Ho and I. Chai, Design and Functionality of a University Academic Advisor Chatbot as an Early Intervention to Improve Students’ Academic Performance, in A. R. Alfred and H. H. Iida (eds), *Lecture Notes in Electrical Engineering*, **724**, pp. 167–178, 2021. 45
- 46 46. R. Thamilselvan, P. Natesan, A. Manimaran, S. E. Naveenkumar, J. K. Shanthosh and S. Vigneshwaran, Designing a Llama 2-Powered Chatbot for Enhanced College Website Support, *Proceedings of the 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kamand, p. 1, 2024. 46
- 47 47. G. De La Puente, A. Silva and R. Felix, Development of a chatbot powered by artificial intelligence to diagnose and improve stress and anxiety levels in university students, *Proceedings of the IEEE XXXI International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*, Lima, pp. 1–8, 2024. 47
- 48 48. G. Ilieva, T. Yankova, S. Klisarova-Belcheva, A. Dimitrov, M. Bratkov and D. Angelov, Effects of Generative Chatbots in Higher Education, *Information*, **14**(9), 2023. 48
- 49 49. J. N. Ndunagu, R. G. Jimoh, U. Chidiebere and G. D. Opeoluwa, Enhanced Open and Distance Learning Using an Artificial Intelligence (AI)-Powered Chatbot: a Conceptual Framework, *Proceedings of the 5th Information Technology for Education and Development (ITED)*, Abuja, pp. 1–4, 2022. 49
- 50 50. M. A. Valles-Coral, L. Salazar-Ram´irez, R. Injante, E. A. Hernandez-Torres, J. Jua´rez-D´ıaz, J. R. Navarro-Cabrera et al., Density-Based Unsupervised Learning Algorithm to Categorize College Students into Dropout Risk Levels, *Data*, **7**(11), 2022. 50
- 51 51. G. De La Puente, A. Silva and R. Felix, Development of a chatbot powered by artificial intelligence to diagnose and improve stress and anxiety levels in university students, *Proceedings of the IEEE XXXI International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*, Lima, pp. 1–8, 2024. 51
- 52 52. G. Ilieva, T. Yankova, S. Klisarova-Belcheva, A. Dimitrov, M. Bratkov and D. Angelov, Effects of Generative Chatbots in Higher Education, *Information*, **14**(9), 2023. 52
- 53 53. G. Ilieva, T. Yankova, S. Klisarova-Belcheva, A. Dimitrov, M. Bratkov and D. Angelov, Effects of Generative Chatbots in Higher Education, *Information*, **14**(9), 2023. 53
- 54 54. G. Ilieva, T. Yankova, S. Klisarova-Belcheva, A. Dimitrov, M. Bratkov and D. Angelov, Effects of Generative Chatbots in Higher Education, *Information*, **14**(9), 2023. 54
- 55 55. J. N. Ndunagu, R. G. Jimoh, U. Chidiebere and G. D. Opeoluwa, Enhanced Open and Distance Learning Using an Artificial Intelligence (AI)-Powered Chatbot: a Conceptual Framework, *Proceedings of the 5th Information Technology for Education and Development (ITED)*, Abuja, pp. 1–4, 2022. 55
- 56 56. J. N. Ndunagu, R. G. Jimoh, U. Chidiebere and G. D. Opeoluwa, Enhanced Open and Distance Learning Using an Artificial Intelligence (AI)-Powered Chatbot: a Conceptual Framework, *Proceedings of the 5th Information Technology for Education and Development (ITED)*, Abuja, pp. 1–4, 2022. 56
- 57 57. J. N. Ndunagu, R. G. Jimoh, U. Chidiebere and G. D. Opeoluwa, Enhanced Open and Distance Learning Using an Artificial Intelligence (AI)-Powered Chatbot: a Conceptual Framework, *Proceedings of the 5th Information Technology for Education and Development (ITED)*, Abuja, pp. 1–4, 2022. 57

- 1 50. D. Ghosh, R. K. Tiwari and P. R. Gundalwar, Enhancing Education 4.0 with Artificial Intelligence, *Proceedings of the 5th* 1
2 *International Conference on Recent Trends in Computer Science and Technology (ICRTCST)*, Jamshedpur, pp. 558–563, 2024. 2
- 3 51. B. Saha and U. Saha, Enhancing International Graduate Student Experience through AI-Driven Support Systems: A LLM and 3
4 RAG-Based Approach, *Proceedings of the International Conference on Data Science and Its Applications (ICoDSA)*, Bali, pp. 300– 4
5 304, 2024. 5
- 6 52. T. Wang, B. D. Lund, A. Marengo, A. Pagano, N. R. Mannuru, Z. A. Teel *et al.*, Exploring the Potential Impact of Artificial 6
7 Intelligence (AI) on International Students in Higher Education: Generative AI, Chatbots, Analytics, and International Student 7
8 Success, *Applied Sciences*, **13**(11), 2023. 8
- 9 53. J. Delcker, J. Heil, D. Ifenthaler, S. Seufert and L. Spirgi, First-year students AI-competence as a predictor for intended and de facto 9
10 use of AI-tools for supporting learning processes in higher education, *International Journal of Educational Technology in Higher* 10
11 *Education*, **21**(1), 2024. 11
- 12 54. J. Santhosh, A. Dengel and S. Ishimaru, Gaze-Driven Adaptive Learning System With ChatGPT-Generated Summaries, *IEEE* 12
13 *Access*, **12**, pp. 173714–173733, 2024. 13
- 14 55. P. F. Oliveira and P. Matos, Introducing a Chatbot to the Web Portal of a Higher Education Institution to Enhance Student 14
15 Interaction, *Engineering Proceedings*, **56**(1), 2023. 15
- 16 56. J. Zhang, Y. Liu, W. Cai, S. Qi, T. Long and B. Ge, Investigation of the Effectiveness of Applying ChatGPT in Dialogic Teaching of 16
17 Electronic Information Using Electroencephalography, *Proceedings of the 6th International Conference on Computer Science and* 17
18 *Technologies in Education (CSTE)*, Xi'an, pp. 150–154, 2024. 18
- 19 57. M. N. Deri, A. Singh, P. Zaazie and D. Anandene, Leveraging Artificial Intelligence in Higher Educational Institutions: A 19
20 Comprehensive Overview, *Revista de Educacio'n y Derecho*, (30), 2024. 20
- 21 58. L. Hermawan, D. Stiawan, R. A. Syakurah, Meilinda and D. S. Ikhsan, Mental Health with Machine Learning: A Prediction-Based 21
22 Intervention Chatbot for Mental Health Conversations, *Proceedings of the 11th International Conference on Electrical Engineering,* 22
23 *Computer Science and Informatics (EECSI)*, pp. 590–595, 2024. 23
- 24 59. A. Almada, Q. Yu and P. Patel, NLP K-Means Algorithm Incorporated into a Proactive Chatbot to Assist Failing Students, 24
25 *Proceedings of the International Conference on Intelligent Computing and Machine Learning (2ICML)*, Qingdao, pp. 24–30, 2023. 25
- 26 60. N. Segovia-Garc'ia, Optimizing Student Support: A Review of the Use of AI Chatbots in Higher Education, *European Public & Social* 26
27 *Innovation Review*, **9**, pp. 1–20, 2024. 27
- 28 61. F. A. A. J. Almahri, D. Bell and M. Arzoky, Personas Design for Conversational Systems in Education, *Informatics*, **6**(4), 2019. 28
- 29 62. J. Gera, E. B. Marwaha, R. Thareja and A. Jain, Predicting and Improving Behavioural Factors that Boosts Learning Abilities in 29
30 Post-Pandemic Times using AI Techniques, *International Journal of Advanced Computer Science and Applications (IJACSA)*, **14**(11), 30
31 pp. 274–282, 2023. 31
- 32 63. A. Almada, Q. Yu and P. Patel, Proactive Chatbot Framework Based on the PS2CLH Model: An AI-Deep Learning Chatbot 32
33 Assistant for Students, in K. A. (ed), *Lecture Notes in Networks and Systems*, **542**, pp. 751–770, 2023. 33
- 34 64. M. Takeuchi, A. Ito and T. Nose, Selection of key sentences from lecture video transcription and its application to feedback to the 34
35 learner, *Proceedings of the 8th International Conference on Education and Multimedia Technology*, Tokyo, pp. 218–223, 2024. 35
- 36 65. D. Ginting, D. Sabudu, Y. Barella, A. Madkur, R. Woods and M. K. Sari, Student-centered learning in the digital age: in-class 36
37 adaptive instruction and best practices, *International Journal of Evaluation and Research in Education*, **13**(3), pp. 2006–2019, 2024. 37
- 38 66. L. Mehnen and B. Pohn, Supporting Academic Teaching with Integrating AI in Learning Management Systems: Introducing a 38
39 Toolchain for Students and Lecturers, *Proceedings of the International Conference on Software, Telecommunications and Computer* 39
40 *Networks (SoftCOM)*, 2024. 40
- 41 67. D. Mirzayeva, R. Ortiqov, D. Usmonova, N. Nizomova, N. Makhmudova and S. Karimjonova, The AI Illustration in Shifting the 41
42 Technical Education System to Digital Era, *Proceedings of the 4th International Conference on Advance Computing and Innovative* 42
43 *Technologies in Engineering (ICACITE)*, pp. 1521–1527, 2024. 43
- 44 68. N. Madaminov and M. Urinov, The Capacity of AI in Education System Towards in Acquiring the Innovative tested Models to 44
45 Enhance the Learning Experience, *Proceedings of the 4th International Conference on Advance Computing and Innovative Technologies* 45
46 *in Engineering (ICACITE)*, Greater Noida, pp. 556–560, 2024. 46
- 47 69. N. S. Alotaibi, The Impact of AI and LMS Integration on the Future of Higher Education: Opportunities, Challenges, and Strategies 47
48 for Transformation, *Sustainability*, **16**(23), 2024. 48
- 49 70. S. M. Aflal, S. Shamugarajah, K. Thiruthanigesan, B. Balasubramaniam, U. Samarakoon and R. G. Ragel, The Impact of AI-Driven 49
50 Educational Transformation in Sri Lanka's Higher Education, *Proceedings of the 6th International Conference on Advancements in* 50
51 *Computing (ICAC)*, pp. 223–228, 2024. 51
- 52 71. S. Sulaymanova, Z. Boboyeva and O. Soliyev, The Integration of Artificial Intelligence towards Interactive Based Higher Education 52
53 System Design, *Proceedings of the 4th International Conference on Advance Computing and Innovative Technologies in Engineering* 53
54 *(ICACITE)*, Greater Noida, pp. 514–518, 2024. 54
- 55 72. M. A. Arbulu´ Ballesteros, B. G. Acosta Enr'iquez, E. V. Ramos Farron'a'n, H. D. Garc'ia Jua'rez, L. E. Cruz Salinas, J. E. Blas Sa'ncchez 55
56 *et al.*, The sustainable integration of AI in higher education: Analyzing ChatGPT acceptance factors through an extended UTAUT2 56
57 framework in Peruvian universities, *Sustainability*, **16**(23), 2024. 57
73. K. G. Fomunyan, Theorising machine learning as an alternative pathway for higher education in Africa, *International Journal of* 58
59 *Education and Practice*, **8**(2), pp. 268–277, 2020. 59
- 60 74. S. Mate, A. Mahajan and Y. Haribhakta, University recommendation system using neural collaborative filtering, *Proceedings of the* 60
61 *3rd International Conference for Advancement in Technology (ICONAT)*, 2024. 61
- 62 75. N. Yarovenko-Kuzminykh, M. Caeiro-Rodriguez, F. A. Mikic-Fonte and M. Llamas-Nistal, Using a generative AI chatbot for SRL 62
63 measurement and intervention, *Proceedings of the International Symposium on Computers in Education (SIIE)*, A Corun'a, 2024. 63
- 64 76. R. Thamilselvan, P. Natesan, E. Gothai, S. E. Naveenkumar, J. K. Shanthosh and S. Vigneshwaran, Developing an AI-Driven 64
65 Chatbot for Enhanced College Website Support Using Machine Learning, *Proceedings of the International Conference on Expert* 65
66 *Clouds and Applications (ICOECA)*, Bengaluru, pp. 719–726, 2024. 66
- 67 77. E. Budiman, Haviluddin, N. Dangan, A. H. Kridalaksana, M. Wati and Purnawansyah, Performance of Decision Tree C4.5 67
68 Algorithm in Student Academic Evaluation, *Lecture Notes in Electrical Engineering*, **488**, pp. 380–389, 2018. 68

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Contents

Section I

Special Issue

Artificial Intelligence in Engineering Education – Part I

Guest Editors

Andrés D'íaz Lantada¹ & José Luis Martín Núñez²¹Escuela Técnica Superior de Ingenieros Industriales,
Universidad Politécnica de Madrid, Spain²Instituto de Ciencias de la Educación, Universidad Politécnica de Madrid, Spain**Editorial** 1409–1410*Ahmad Ibrahim***Guest Editorial** 1411**Special Issue on: Artificial Intelligence in Engineering Education – Part I***Andrés D'íaz Lantada and José Luis Martín Núñez***AI-Powered Telepresence Laboratory: Generative AI Co-Pilot for Automated Experiment Guidance and Instruction** 1412–1432*Phumrapee Meyer, Pravee Kruachottikul, Chakkrit Tantithamthavorn, Kittikul Kovitangoon, Ratchatin Chancharoen and Gridsada Phanomchoeng*

This study presents an AI-powered telepresence laboratory designed to enhance engineering education by integrating a Generative AI co-pilot for automated experiment guidance and instruction. The system provides real-time procedural support, AI-assisted experiment monitoring, and interactive feedback, reducing instructor and lab technician workload while ensuring students achieve key laboratory objectives, such as following calibration procedures, interpreting sensor data, and understanding measurement uncertainty. The evaluation results confirm that the system improves student engagement, ensures procedural accuracy, and maintains learning outcomes comparable to traditional laboratory settings. Additionally, it redefines the roles of instructors and lab technicians, shifting their focus from direct supervision to curriculum development and AI system enhancement. By providing an accessible and interactive laboratory experience, this study demonstrates the effectiveness of scalable, AI-powered telepresence laboratories while acknowledging the continued need for expert oversight in complex experimental analysis.

Keywords: Generative AI; telepresence laboratory; engineering education; remote learning; collaborative; virtual laboratories; AI in education; large language models

Federated Learning for Accessible Engineering Education: A Survey on AI-Driven Personalization for Students with Disabilities 1433–1446*Belghachi Mohammed and Seddiki Noureddine*

Federated learning (FL) offers a promising approach to improving accessibility in engineering education for students with disabilities by enabling personalized learning while preserving data privacy. This paper presents a comprehensive survey of current research on FL and AI-driven personalization in the context of inclusive education. It reviews applications such as adaptive assessments, accessible course materials, and assistive technologies, supported by real-world case studies that highlight feasibility and impact. Key challenges include computational overhead, data heterogeneity, algorithmic bias, and privacy risks. The review identifies gaps in existing work, including limited representation of certain disability types and methodological constraints. Future directions are proposed, focusing on explainable AI, edge computing, multimodal data integration, and interdisciplinary collaboration. The findings support the development of equitable, scalable, and privacy-respecting systems to foster inclusive engineering education.

Keywords: federated learning; accessible education; AI-driven personalization; students with disabilities; engineering education; privacy-preserving systems

Implementing Artificial Intelligence in Higher Education: A Pathway to Effective PBL 1447–1461*Silvia Lavado-Anguera, María-José Terro'n-Lo'pez and Paloma-J. Velasco-Quintana*

This paper aims to investigate the integration of Artificial Intelligence (AI) into Project-Based Learning (PBL) methodologies within STEAM (Science, Technology, Engineering, Art, and Mathematics) education. It seeks to evaluate how AI can enhance the teaching-learning process, optimize project management, and foster digital competence among students and educators. An action research methodology is employed, consisting of iterative cycles of planning, acting, observing, and reflecting. The study focuses on developing, implementing, and assessing AI-supported PBL strategies. Data is collected through classroom observations, participant feedback, and performance evaluations to analyze the effectiveness and adaptability of AI-enhanced PBL approaches. The study provides empirical insights into the benefits and challenges of AI integration into PBL. Results suggest that AI can enhance project management, automate repetitive tasks, and support individualized learning. Challenges include technological limitations, user adaptability, and the need for adequate teacher training. The study is limited to the initial phase of implementation, with long-term outcomes yet to be measured. Findings are based on specific STEAM settings, which may limit generalizability. The paper highlights strategies for enhancing PBL through AI, including improving project planning, fostering digital literacy, and providing adaptive learning support. It addresses ethical considerations related to data privacy, informed consent, and algorithmic bias, emphasizing the need for responsible AI use in educational settings. This paper offers a systematic framework for integrating AI into STEAM-based PBL, contributing to the growing body of research on AI in education. It provides practical guidance for educators and policymakers, highlighting the transformative potential of AI in project-based learning.

Keywords: artificial intelligence; project-based-learning; higher education; implementation

Zachery Quince, Kathy Petkoff, Anna Lidfors Lindqvist, Emily Faulconer, Winn Chow and Sasha Nikolic

Generative artificial intelligence (GenAI) platforms are widely used to create images based on textual inputs. While these tools hold great potential to influence societal perceptions, they also risk perpetuating stereotypes and biases, particularly in fields like engineering, where stereotypical depictions are commonplace. Engineering images often reinforce traditional views of gender, race, and professional roles, raising concerns about whether GenAI tools can produce visuals that are truly inclusive and representative of diverse groups. This study aims to investigate the ability of two GenAI tools, Copilot and Canva, to generate diverse and inclusive representations of engineering teams. By analysing the quality and diversity of images generated using a systematic approach, the research provides insights into the biases embedded within these tools. The quality of the generated images had several flaws, including multiple missing or additional limbs, facial features, or fingers. This study revealed the flawed and generic images that GenAI tools can generate when asking to generate a simple engineering team. Racial, gender, and age-based stereotypes of engineers were a constant theme throughout the images. There was limited diversity and inclusion of Indigenous peoples, hair colour and length, and body shape and size. The findings are intended to set a baseline for future evaluations and improvements in GenAI platforms.

Keywords: GenAI; Ethics; Diversity; Equity; Gender; Image Generation; Stereotypes

AI-Driven Predictive Models and Chatbots for Early Intervention and Student Success in Higher Education: A Systematic Review*Felipe Emiliano Arevalo-Cordovilla and Marta Penã*

Student attrition in higher education remains a persistent global issue, with dropout rates exceeding 40% in several countries. This necessitates the development of early evidence-based intervention strategies. Artificial Intelligence (AI) has emerged as a promising tool; however, its implementation is often approached in a fragmented manner. This systematic review analyzes the synergistic use of machine learning-based predictive models and conversational chatbots as an integrated system to support students' success. A total of 46 studies indexed in Scopus, Web of Science, and IEEE Xplore (2019–2024) were examined according to the PRISMA 2020 protocol. The results indicate that techniques such as neural networks and random forests achieve predictive accuracies above 90% for academic risk detection, with hybrid models reaching F1 scores of up to 0.99. Concurrently, chatbots are evolving into personalized virtual tutors with contextual response capabilities and 24/7 availability, achieving F1 = 99.75% and boosting academic performance by 25%. The integration of these technologies has a positive impact on student retention, motivation, and institutional efficiency. The future of support systems lies in integrated, ethical, pedagogically grounded, and student-centered AI ecosystems that can transform educational interventions into more inclusive and effective environments.

Keywords: conversational chatbots; dropout prediction; early intervention; educational artificial intelligence; higher education; machine learning; predictive models; student success

SHAP Analysis of Software Engineering Capstone Team Building Criteria*M. Khalid Shaikh and Mirka Saarela*

To assist the students of software engineering in forming their cohesive capstone teams, a set of 127 criteria is available in seminal research in the literature. Those criteria were automated into a team recommendation system *Psychographd* which groups students based on their matching responses to a psychographic self-evaluation questionnaire. In the current research, these criteria are examined to explain which are most influential in fostering team cohesion. The data comprises the original student responses to the psychographic self-evaluation questionnaire collected before team assignments and their responses to the Group Environment Questionnaire used to assess the team cohesion after they began working in their recommended teams. SHAP analysis (SHapley Additive exPlanations), revealed how specific criteria promote or diminish cohesion, providing transparency into the recommendation process. The results demonstrate *Psychographd's* effectiveness and underscore the potential of explainable AI in optimizing educational team formation strategies.

Keywords: explainable AI; SHAP; capstone teams; software engineering; team building criteria

Integrating Generative AI into Engineering Education: A Case Study in Web Application Development*Roberto Barchino, Jose A. Medina, Rosa Estriegana and M. Lourdes Jimenez*

The integration of Generative Artificial Intelligence (GAI) tools into higher engineering education holds transformative potential, especially in supporting programming and software development courses. This paper presents an exploratory study of GAI application in a fourth-year elective course in the Computer Engineering program at the University of Alcalá, focused on the design and development of web applications. In the course, students are required to design and implement a web application using the Model-View-Controller (MVC) design pattern with both client-side and server-side technologies. The study explores the impact of ChatGPT as a learning assistant, providing support in debugging, understanding, and implementing the MVC pattern. A conceptual model is proposed to evaluate the influence of ChatGPT across three dimensions: support in the learning process, support in academic performance improvement, and academic integrity. Additionally, the model examines how these three factors influence student satisfaction. To validate the model, a survey was designed and completed by all students enrolled in the course ($n = 72$). A mixed-method analysis was conducted, including descriptive statistics, relations analysis, and qualitative analysis based on an open-ended question. The main findings show that students perceive their learning and educational outcomes positively when using ChatGPT, although areas for improvement remain in satisfaction and academic integrity. Correlations indicate that increased learning is associated with higher satisfaction, while the perception of academic integrity appears to be independent. The qualitative analysis reveals that ChatGPT is regarded as a useful tool, though concerns arise around dependency and reduced cognitive effort. A regulated integration of ChatGPT is recommended to maximize benefits while minimizing potential negative impacts. This paper contributes to the growing body of evidence on the impact of GAI in education, offering a practical framework for integrating ChatGPT in project-oriented learning environments.

Keywords: ChatGPT; engineering education; web development; MVC pattern; GAI

Examining Engineering Students' Academic Performance Using Machine Learning Algorithms as a Data Analysis Tool*Carlos Felipe Rodriguez-Hernandez, Vinay Ram Gazula and Prateek Shekhar*

As the demand for engineers continues to grow, understanding the factors that influence the academic performance of engineering students has become increasingly important. While much of the existing research has focused on predicting common indicators such as grade point average (GPA), the time it takes students to complete their academic programs (known as time-to-degree (TTD)) has received comparatively less attention. Furthermore, recent advancements in artificial intelligence and machine learning have provided new data analysis tools for performing predictive analysis on large educational datasets. This study leverages a range of machine learning algorithms, including multiple linear regression, binary logistic regression, decision trees, random forest, XGBoost, and LightGBM, to analyze GPA and TTD data from records of 7,871 undergraduate engineering students at a public research university in the United States. First, we evaluate the performance of these algorithms in two tasks: predicting GPA (regression task) and classifying TTD (classification task). Second, we examine how variables related to students' academic background (such as high school GPA, SAT scores, and major), demographic background (sex and underrepresented status), and socioeconomic background (eligibility for educational opportunity programs) contribute to predicting GPA and classifying TTD. The results indicate that multiple linear regression and binary logistic regression outperform single decision-tree methods. However, ensemble methods that combine multiple decision trees, such as random forest and LightGBM, provide better performance than regression-based models, particularly in predicting GPA. Moreover, the variable importance analysis using the SHapley Additive

exPlanations (SHAP) method reveals that students' background characteristics differentially predict GPA and TTD, with academic background variables holding the highest importance. The findings highlight the potential of machine learning techniques in examining educational datasets and offer insights for future research on leveraging machine learning as a data analysis tool in engineering education research.

Keywords: machine learning; engineering education; academic performance

Enhancing AI Algorithm in Digital Signal Processing Education, Through Extreme Programming: Constructive Approach 1532–1546 in IoT Context

Mario Stojanovic', Ana Matovic', Marija Matovic', Edis Mekic', Vanja Baz'dar and Zakaria Maamar

This research investigates the impact of integrating Extreme Programming (XP) into a Constructive Learning framework on Student Learning Outcomes (SLO) in Digital Signal Processing (DSP) and Artificial Intelligence (AI) applications, specifically focusing on application in Internet of Things (IoT) context. The study involved final-year undergraduate engineering students engaged in developing a virtual laboratory environment, leveraging XP practices such as iterative development, pair programming, continuous feedback, and test-driven development. Empirical findings, collected through surveys and structural equation modeling, demonstrated significant improvements across affective, cognitive, and behavioral dimensions. Students exhibited increased motivation, reduced anxiety toward complex DSP and AI tasks, deeper conceptual understanding, and enhanced practical skills essential for real-world IoT implementations. Overall, the results affirm that Agile methodologies like XP can effectively foster student engagement, practical competencies, and positive attitudes toward complex technical education, supporting broader integration in engineering curricula.

Keywords: Digital Signal Processing; Extreme Programming; Agile Methodologies; Internet of Things; Virtual Laboratory; Constructive Learning

AI-Based Performance and Grade Prediction for Undergraduate Industrial Engineering Students in Machine Component Design Course 1547–1555

Amjad Alsakarneh, Abedallah AlKader, Mo'en Alnasraween, Hamed Mubarak Al-Awidi and Alaa A. Towaiq

The availability of student data in educational institutions presents a valuable opportunity to apply machine learning (ML) techniques for predicting academic performance before the start of a new semester. Some variables can support early identification of students' potential performance and guide them in planning. In this article, we present predictive analysis models for the academic performance of engineering students at Yarmouk University during the years between 2019 and 2024. The machine learning models were applied using data collected from the university's registration office, with some demographic information. Various machine learning models were employed, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Artificial Neural Networks (ANN) to identify the significant attributes affecting student performance in the machine component design course. The results present that factors such as CGPA and registered course load (in credit hours) significantly affect student performance. Among the models applied, ANN achieved the highest accuracy with an RMSE of 6.1, and the model SVR the lowest RMSE of 8.2. This research aims to assist students in identifying the potential outcomes early and provide advice to support students in registration planning.

Keywords: academic performance prediction; AI in education; engineering students, student data analytics

Section II

Contributions in: Attitude Scale, Digital Design, Teamwork, Capstone Projects, Creativity, Entrepreneurship, Identity, First-Year engineering, Doctoral Education, Adaptive Learning, Faculty Development, Industry Academia Alignment

Development and Validation of an Attitude Scale toward Generative AI for University Students 1556–1568

Yao-Chung Cheng, Chien-Yu Lu, Kai-Jie Chen and Chuan-Tsai Lin

This study developed and validated the Generative AI Attitude Scale (GAIAS) to assess university students' attitudes toward generative AI. Using an online survey of 700 students from 85 Taiwanese universities (238 males, 462 females, mean age 24.23), exploratory factor analysis identified a 12-item, two-factor structure that captures positive and negative attitudes, explaining 61.71% of the variance. The scale demonstrated satisfactory internal consistency for the higher-order construct (Cronbach's $\alpha = 0.772$) and strong composite reliability for the two subscales (CR = 0.87 and 0.88). Convergent validity was acceptable for both dimensions (AVE = 0.528 and 0.552). Confirmatory factor analysis supported a higher-order model integrating the two attitudinal dimensions into a robust overarching construct. Concurrent validity was evidenced through favorable correlations with the Artificial Intelligence Anxiety Scale. Substantively, students in natural sciences and engineering reported more positive attitudes than peers in the humanities and social sciences, indicating discipline-specific orientations toward emerging technologies. GAIAS can help institutions gauge receptiveness to generative AI, tailor pedagogy to disciplinary needs, and monitor attitudinal change as AI tools diffuse across curricula. Future research should broaden sampling frames and employ mixed methods to deepen understanding of how attitudes and anxiety jointly shape technology adoption and educational outcomes.

Keywords: artificial intelligence; generative AI; attitude scale; Generative AI attitude scale

Integrating Industrial Tool-Based Formal Verification into ECE Design Verification Curriculum 1569–1584

Shruti Sharma, Mohamed Ghonim, Xiaoyu Song, Jin Zhang and Andrew Greenberg

Simulation, the traditional mainstay of digital design verification, faces increasing challenges as design complexity escalates. Formal verification, a widely adopted methodology for functional verification of Register-Transfer Level (RTL) designs in the industry, offers a compelling alternative. This paper addresses the critical need to integrate industry-grade formal verification techniques into academic curricula, a gap currently underserved. While some formal verification courses exist, they often rely on academic tools like SAT solvers and model checkers, limiting students' exposure to industry-standard practices. This paper details the development of a unique graduate-level course at Portland State University (PSU) that introduces industrial assertion-based formal verification, specifically utilizing tools like VC Formal. This practical, industry-focused approach distinguishes the course from traditional offerings. We outline the course development process, beginning with a capstone project that served as a pilot study to gather essential learnings and feedback. We then detail the curriculum design, including the course focus, grading structure, and the design of homework assignments and examinations. Student survey results demonstrate the course's significant positive impact on perceived industry relevance and job interview preparedness. Ultimately, this initiative aims to bridge the gap between academic theory and industrial practice in the rapidly evolving field of formal verification. This study explores the initial integration of industrial formal methods into a computer engineering curriculum.

Keywords: industrial formal verification; simulation; assertion based verification; engineering curriculum; digital design

Francisco Cima, Pilar Pazos and Ana Mar'ia Canto-Esquivel

The dynamic context faced by engineers in the workplace requires the ability to work effectively in teams. Past research in engineering education has examined teamwork in project-based settings, but few capture the complexity of tasks in the engineering field. Additionally, there is a lack of theoretically sound and psychometrically valid measures to determine the true level of teamwork competencies. This work fills the gap of prior studies through two contributions. First, it examines teamwork skill development through participation in authentic engineering projects. Second, it employs a valid and reliable instrument grounded in team science to capture critical teamwork skills. This research evaluates the impact of a scaffolded approach to capstone projects on the development of teamwork skills when compared to a traditional approach. A quasi-experimental study was conducted to determine the effect of scaffolded collaboration on engineering students' teamwork skills. The sample included 122 students, of whom 66 were part of the comparison group, and 56 were in the treatment group. Teams of engineering students were assigned either a modified capstone with scaffolds or a traditional capstone. The scaffolds model best practices as part of project-based activities and tools built into the course. Results indicate that participants in the treatment group (capstone with scaffolded collaboration) demonstrated significantly higher skills in planning, execution, and interpersonal competencies than students in the comparison group (regular capstone). Our results suggest that using scaffolds to support project work can help strengthen engineering students' teamwork skills and prepare them to face collaborative work in their future careers. This study suggests a valid and reliable measure of teamwork skills that can be used by engineering programs to examine skill development and document ABET outcomes related to teamwork.

Keywords: teamwork skills; capstone projects; scaffolds; engineering teams

Unpacking the Creativity Paradox: A Systems Analysis of Misalignment, Barriers, and Opportunities in Graduate Engineering Education

1593–1604

Autumn R. Deitrick and Catherine G. P. Berdanier

While creativity has been studied within undergraduate engineering education, it has rarely been studied at the graduate level. Exploring students' perceptions of creativity in graduate engineering education can allow for the identification of broader systems-level barriers to creating a thriving creative climate. This exploratory study aims to unpack engineering graduate students' perceptions, both positive and negative, of creativity in graduate engineering education. By employing a systems theory framework, this research seeks to understand how structural and systems-level influences shape students' experiences and perceptions surrounding creativity. Data were collected through written survey responses from $n = 115$ engineering graduate students from R1 engineering programs across the United States. Using conventional qualitative content analysis, we identified emergent perceptions surrounding creativity in graduate engineering education. These perceptions were then analyzed through a systems analysis lens to uncover systems-level barriers and opportunities for fostering creativity. Our analysis revealed a significant misalignment between the recognized importance of creativity and its actual support in graduate engineering education. While students emphasized creativity's critical role in research, problem-solving, and career preparation, they also identified systemic barriers, including rigid degree structures, limited resources, inconsistent mentorship, and an institutional focus on measurable outputs (e.g., publications) over creative exploration. To address these challenges, advisors and administrators should integrate explicit discussions of creativity into academic programs, reframe degree requirements to value creative contributions, and promote structural changes that prioritize creative exploration.

Keywords: creativity; engineering; graduate students

Converting Students' Entrepreneurial Self-Efficacy into Tangible Entrepreneurial Actions

1605–1615

Lili Feng, Serrene Leong, Kenny S. L. Cheah and Jianbing Deng

This study explores the role of entrepreneurial self-efficacy (ESE) in bridging the gap between entrepreneurial intention and behavior (EIB) in the context of entrepreneurial education (EE). Despite the growing focus on EE, the conversion rate of intention to actual behavior remains suboptimal. Based on survey data from 256 vocational college engineering students in China and utilizing established scales for measurement, the study employs structural equation modeling (SEM) to test the proposed hypotheses. Results confirm ESE as a significant predictor of EIB ($\beta = 0.775$, $p < 0.001$), with strong explanatory power ($R^2 = 0.764$, $R^2 = 0.601$). The findings highlight the importance of ESE in transforming entrepreneurial aspirations into tangible actions and stress the need for experiential learning to enhance students' confidence and skills, fostering practical entrepreneurs who drive innovation and business success.

Keywords: entrepreneurial self-efficacy; entrepreneurial intention and behavior; vocational college students; entrepreneurship education; experiential learning

Engineering Identity Formation across the Undergraduate Years

1616–1630

M. Jean Mohammadi-Aragh, Rachel L. Kaffez, Abigail Clark and Soundouss Sassi

First-year engineering programs are one of the earliest opportunities for undergraduate engineering educators to support engineering identity formation and community building, both of which are important for retention. This research examines how engineering identity emerged across undergraduate engineering students' degree experiences starting in their initial year in university, and how engineering communities impacted engineering identity emergence. We conducted longitudinal interviews with students one, two, and three years after they began their engineering degrees. Through our analysis, we identified three themes from the participant interviews: (1) engineering identity must be claimed by the individual not gifted externally, (2) engineering identity was described by some participants in terms of an engineering mindset, a concept taught in those participants' first-year engineering course, and (3) first-year communities did not withstand time. More specifically, we found that for the participants in this study to reach the state where they claimed to be an engineer required experiences that served as recurrent positive feedback to push them to a *tipping point*, and that these engineering expertise confirming experiences were rarely directly attributed to engineering coursework or engineering student community membership. However, deliberate instruction about engineering mindsets may have indirectly supported engineering identity formation. Future quantitative investigations are warranted to (1) understand how educators can leverage engineering mindsets to support identity development and (2) understand the transferability of our finding that first-year communities do not withstand time and the mechanics of why this occurs.

Keywords: identity; community of practice; first-year engineering

Examining Qualifying Exams: A Qualitative Case Study of Graduate Students and Faculty Perspectives

1631–1642

Mayra S. Ariles and Kai Jun Chew

Qualifying exams are a major milestone graduate students need to pass on their doctoral journey, yet little research has examined them through an assessment lens. Using a case study approach, we investigated the perspectives of doctoral students and faculty in one chemical engineering doctoral program. Guided by Linda Suskie's five characteristics of good assessments – usefulness, cost-effectiveness, accuracy, value, and clarity of goals – we conducted and analyzed semi-structured interviews with eight graduate students and six faculty members. The study found that although both faculty and students view the qualifying exam as useful and efficient, the absence of clearly defined objectives limits its value and creates confusion for students. Faculty generally agree the exam assesses readiness for independent research, but their inability to articulate specific goals leads students to experience it as a high-stakes formality rather than a meaningful assessment, highlighting the need for greater clarity and intentionality. This study contributes a novel application of Suskie's assessment framework to graduate education and underscores the importance of aligning

assessment design with clear goals and inclusive practices to support doctoral student development. We present specific implications for practice to ensure equity and fairness as a product of this milestone regarding the clarity of its objectives and consider broader alternatives to this milestone.

Keywords: doctoral education; qualifier exams; assessment

A Depth of Study Analysis on First-Year Engineering Quantitative Literacy Tasks

1643–1652

Raenita A. Fenner, Peggy O'Neill, Elliot P. Douglas and Kerrie Douglas

This study investigates the nature and cognitive demand of quantitative literacy (QL) tasks in first-year engineering courses. Despite extensive research into QL in the general population, there is a limited understanding of its incorporation into engineering curricula, particularly the specific aspects expected of first-year engineering students. By employing a deductive Qualitative Content Analysis and an a priori coding scheme based on a systematic QL definition, this research categorizes QL instances within assignments. Concurrently, it uses an adapted version of the Task Analysis Guide for Science (TAGS) to evaluate the cognitive demand of these QL tasks. The findings highlight the primary requirements of QL tasks as cognitive interpretation and reasoning, mostly demonstrating a low-to-moderate cognitive demand. This suggests the tasks are significantly scaffolded, signaling an instructional focus on fundamental knowledge and engineering practices within the QL tasks.

Keywords: quantitative literacy; first-year engineering; qualitative content analysis; task analysis guide for science

Design and Implementation of an AI-Enhanced Teaching of Signals and Systems Course

1653–1664

Xin Xu, Dong Chen, Lei Yang, Biao Wang, Shuangbao Shu, Chengliang Pan, Jin Zhang and Haojie Xia

This paper presents a three-year pedagogical reform study investigating the impact of artificial intelligence (AI) and adaptive learning technologies on student outcomes in the Signals and Systems course at Hefei University of Technology (HFUT). Approximately 130 sophomore students majoring in Measurement and Control Technology and Instruments were divided into an experimental group receiving AI-enhanced instruction and a control group receiving traditional teaching. The study implemented and evaluated three key AI-driven interventions: (1) a machine learning-based cognitive blind-spot detection system using YOLO object detection models to automatically identify typical error patterns in circuit design and frequency spectrum analysis tasks, (2) adaptive virtual laboratory exercises with dynamically adjustable difficulty levels and incorporating real case studies based on individual student performance and feedback, and (3) a rigorous assessment framework employing NI Multisim practical exams evaluated with a detailed rubric. Results demonstrated that the AI-assisted cohorts demonstrated substantially improved performance. Notably, the AI-assisted group exhibited an approximately 32% lower error rate in the NI Multisim practical exam compared to the control group, a statistically significant improvement. Additionally, students in the AI-enhanced group showed higher engagement and confidence in tackling complex signal processing problems. The study concludes that integrating YOLO-based error detection and adaptive virtual labs significantly enhances learning outcomes. It contributes a validated pedagogical model for AI-driven personalized feedback in engineering education, supported by empirical evidence and an evaluation rubric, offering a framework for broader adoption in similar courses.

Keywords: engineering education; signals and systems; adaptive learning; object detection; YOLO

Model to Assist in the Optimization of Learning Environments for Engineering Teaching (OLEET)

1665–1674

Kristi J. Shryock, Lance L.A. White and Karan L. Watson

Engineering educators often juggle competing demands while striving to deliver meaningful classroom experiences, particularly in research-intensive institutions where teaching may be undervalued. This work introduces the Optimizing Learning Environments for Engineering Teaching (OLEET) model, a systems-level framework developed to support faculty iteratively aligning their instructional strategies with three interconnected domains: student composition, engineering topic, and instructor skills. Rather than prescribing rigid methods, OLEET empowers instructors to leverage their engineering identity and disciplinary expertise to craft pedagogical approaches responsive to student needs and content complexity. This model is grounded in an inductive qualitative study of 11 engineering faculty at a large R1 institution. Their reflections reveal conflicts between educator and researcher identities and highlight intuitive practices that OLEET formalizes. The main themes found in this study are the following: (1) Connecting Theory to Practice, (2) Active Learning and Engagement, (3) Motivational Strategies and Support, (4) Content Structuring and Scaffolding, and (5) Identity-Informed Teaching. The model's structure encourages adaptive and reflective teaching aligned with engineering design mindset, making it a practical and actionable tool for faculty development in engineering education. OLEET fills a crucial gap in faculty development literature by bridging established pedagogy with disciplinary identity to enhance instructional effectiveness in engineering classrooms.

Keywords: engineering educator identity; faculty development; responsive teaching; instructional design in engineering

Enhancing Learning and Deliverable Quality in Software Engineering through Oral Inquiry Audits

1675–1687

Pauline C. Wade, Hillary E. Merzdorf and Tracy Hammond

Industry-aligned quality assurance (QA) education remains underexplored in software engineering (SE) curricula, contributing to graduates' unpreparedness for QA roles due to misalignments between academic training and industry practices. This study examines the impact of Oral Inquiry Audits (OIAs) – a pedagogical tool derived from industry practices involving oral discussions on QA processes – on undergraduate SE students' group learning and project deliverable quality. Using a quasi-experimental design, SE students developing web applications for real clients within an ISO 25010:2023-aligned QA framework were divided into control (no OIAs) and treatment (OIAs) groups. Data collection included assessments of QA knowledge and customer feedback, with statistical analyses comparing results across groups. This study found that OIAs enhanced group learning and project deliverables in team-based settings, with the treatment group showing greater improvements than the control group, particularly in Integrity and Usability. OIAs can serve as a replicable academic tool to bridge academia-industry gaps by providing experiential, standards-aligned QA training, enhancing graduates' readiness for QA roles, and integrating ISO frameworks into SE education.

Keywords: industry-academia alignment; oral inquiry audits; pedagogy; quality assurance; software engineering; software quality; undergraduate education; zone of proximal development

Guide for Authors

1688

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