



MACHINE LEARNING IN EDUCATION: INNOVATIONS, IMPACTS, AND ETHICAL CONSIDERATIONS

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Abstract

Machine Learning (ML) has recently emerged as a powerful tool with significant potential to revolutionize education, bringing about fundamental changes in pedagogy and research. Its applications span various domains within academia, including administration, instructional method enhancement, and grade prediction. This study illustrates how ML can enhance the effectiveness of research, instruction, and study strategies by adapting to student needs and leveraging new communication tools within virtual learning environments. The literature review encompasses various empirical studies outlining the integration of Artificial Intelligence (AI) and ML within the educational sector. This research paper maps out how educators are leveraging these capabilities while documenting the associated risks and learning outcomes across various educational tiers. You can also refer to the original context in the file named 'Suhani Research Paper OG.pdf' for a comprehensive view. We advocate that current educational practices in engineering and computing with GenAI can indicate to us a roadmap of its potentialities, uses, and risks from the standpoint of both teachers and students. Our purpose with the outcomes and conclusions of this scoping review is to support educators, faculty members, and other stakeholders in engineering and computing education to co-create educational methodologies that articulate GenAI with curricula, AI literacy, and prompt engineering encompassing students' learning domains such as cognitive, affective, or behavioral. This sample paper is mapped against the IJREK standard student template format and expands on the empirical findings.

Keywords: Machine learning; generative AI; education; personalized learning; intelligent content generation; AI literacy; student performance prediction

I. INTRODUCTION

A. Background / Context With the introduction of modern practices in data collection and tremendous growth in the computational capability of computers, a paradigm shift towards novel learning techniques has been observed. This has led to the development of ML, which is essentially a subset of AI that enables computers to learn from data without explicit programming. Regarding education, ML has been used to analyze large datasets to make predictions and decisions, identify patterns, and personalize teaching and learning experiences. The global AI in education market was valued at USD 5.88 billion in 2024 and is expected to expand at a Compound Annual Growth Rate (CAGR) of 31.2% from 2025 to 2030. This growth is fueled by rising demand for personalized learning solutions, the rapid shift toward e-learning platforms (accelerated by the COVID-19 pandemic), and increasing investments in EdTech startups. By technology, ML led the market with a 64.7% revenue share in 2024, owing to its critical role in enabling personalized and adaptive learning experiences. Since the release of diverse generative AI (GenAI) tools such as ChatGPT, Google Gemini, DALL-E, and GitHub Copilot, there has been much debate around the impacts and implications of these tools on education. Currently, extant literature remarks on the affordances, challenges, and opportunities of GenAI. The term 'generative' refers to the capability of AI to produce novel outputs rather than simply reproducing, categorizing, processing, and analyzing inputs. These outputs can come from several sources, including not only text but audio, video, and images, or in the case of engineering and computer science, programming code or design assistance. At the technical level, GenAI works based on Large Language Models (LLMs) such as Generative Pretrained Transformer (GPT-4) or (GPT-5), Gemini, Claude, Or LLaMa 2. These models are sophisticated AI systems that can process and generate human-like language responses, working through prompt engineering. The idea behind prompt engineering is to enable

computers to interpret and understand human language and it has a close relationship with Natural Language Processing (NLP), which is an Artificial Intelligence field that examines how computer systems can interpret and control the natural language such as text or speech. B. Problem Statement Despite the rapid technological advancements in education, teachers were historically unable to give each pupil individualized attention because of the growing administrative load. The automation of the routine duties such as class planning and grading using AI tools have offered the teachers the luxury of spending more time to concentrate on high-impact endeavors, such as mentorship, student support, and discussion facilitation. They can even address customized queries from the students, thanks to the Virtual assistants with AI capabilities. It helps educators more efficiently answering student questions in a personalized way. Furthermore, the field of education is being revolutionized through data-driven decision-making. The large volume of student data may be collected and analyzed using AI which provides educators, administrators, and policymakers with insightful information. It is facilitating educators in developing better curriculum, allocating the resources efficiently, and enhancing teaching strategies. Beyond the innovation obsession to use GenAI in educational institutions, we have noticed a gap in the current literature in describing how engineering and computing Educators are integrating GenAI in their courses, or what educational outcomes students have developed. Therefore, there is a need for an integrated, evidence-based review that can assist educators and researchers in designing comprehensive strategies that encompass both technical skills and AI literacy. C. Objective / Aim Our objectives with this research are the following: (1) Identify the overall features of the studies in terms of bibliometric trends, such as cited articles, articles per year, leading countries, journals, authors, and cluster topics. (2) Inform researchers and/or Educators about the educational features of the studies identified, including features such as type of intervention, participants, research approach, or main learning outcomes. (3) Expose educational strategies elicited by the researchers utilizing GenAI. And (4) Expose issues, challenges and

improvement opportunities for GenAI in engineering and computing education based on the evidence. We intend to provide intuitive knowledge for scholarly research, instructional strategies, policy formation, and AI ethics. In addition to summarizing existing literature, this establishes the framework for further exploration and practical use of ML in learning environments. The potential of ML and its weaknesses, including ethical and accessibility issues, are also assessed in this study. To shape the future of AI-driven education and make sure that technology enhances learning results, stays inclusive, and morally responsible at the same time, it is imperative to understand and address these concerns. D. Significance / Contribution Improving the effectiveness of instruction methods through personalized attention is one of the leading trends in AI education. The combination of ML with other technologies such as Augmented Reality (AR) and gaming has opened the new horizon of instruction design and other applications in education settings for meaningful learning. This combined with AI has helped in developing immersive and engaging learning experiences which are important for Deep Learning (DL). When amalgamated with Virtual Reality (VR) and AR, this allows students to explore historical sites, do virtual science experiments, and participate in lifelike simulations. This work also enriches the existing body of knowledge by addressing significant gaps in the literature about the deployment of ML in education, concentrating notably on the scalability of ML solutions across varied educational contexts and their applicability in low-resource settings. It helps develop more equal, inclusive, and internationally relevant educational technology corresponding to broader aims for sustainable and accessible learning systems. E. Paper Organization The remainder of this paper presents related work, the proposed system and methodology, implementation details, results and analysis, limitations, future scope, and conclusion.

II. LITERATURE REVIEW / RELATED WORK

A. Overview of Existing Research ML can be used to perform various tasks classified into different categories. There are three main types of ML: supervised, unsupervised, and Reinforcement Learning (RL). Supervised learning algorithms are trained using a labelled dataset where the input data are accompanied by the correct output thus mapping new inputs to their correct outputs. Supervised learning algorithms are widely used in educational systems where labeled datasets such as student grades, test results, or engagement levels are available. The most used algorithms belonging to this category include linear regression, logistic regression, Decision Tree (DT), and neural networks. In contrast to this, the algorithms are fed with unlabeled datasets in unsupervised learning which find patterns or structures within the data, without any guidance or labelled outputs. When analyzing large and complicated datasets, unsupervised learning is vital, specifically for anomaly detection, dimensionality reduction, and grouping. The third category is RL that relies on interaction with the environment to achieve certain goals. In this approach, an agent learns over time through trial and error to provide the best results by making decisions and getting feedback in the form of rewards or penalties. AI literacy is the ability to comprehend, assess, interact with, and make informed decisions using AI technologies. AI literacy involves understanding the basic principles of AI, recognizing its applications, and being aware of the ethical, social, and privacy implications of the system using it. This review highlights how the concept of AI literacy is helpful if we analyze the limitations and pitfalls of GenAI reported by educational researchers, which include plagiarism and cheating, privacy issues, potential bias, diversity issues, or spread of false information. B. Summary of Key Research Works Personalized learning, powered by AI technologies such as adaptive learning systems, intelligent tutoring systems, and personalized recommendations, has the potential to revolutionize education by offering tailored, engaging, and effective learning experiences for students. Adaptive learning systems dynamically adjust the content, pace, and difficulty of educational material based on a learner's performance, preferences, and learning style. AI algorithms analyze student interactions, such as quiz scores, time spent on tasks, and correct or incorrect answers, to identify strengths and weaknesses. Based on this analysis, the system modifies the learning path in real-time. Platforms like Knewton and DreamBox use adaptive learning to create personalized pathways in subjects like math and language arts. Additionally, ALEKS, PAT2Math, and Duolingo adapts language lessons based on a user's progress and mistakes, ensuring an engaging and appropriately challenging experience. Another form of AI-driven personalized learning is intelligent tutoring systems, which simulate one-on-one tutoring by providing real-time feedback and guidance. These systems leverage AI to model students' knowledge and

cognitive processes, allowing for personalized feedback and hints. Examples include Carnegie Learning's MATHia, ALEKS, and PAT2Math, which helps students grasp mathematical concepts through personalized exercises, and Socratic by Google, an AI-powered mobile app that assists students in understanding complex topics through guided problem-solving. C. Identified Research Gap While much of the present research illustrates ML's potential to improve educational results, it often remains confined to narrow, well-resourced situations, which restricts its generalizability. This work advances the field by exploring how ML models can adapt to various linguistic and infrastructural settings and by proposing strategies such as lightweight model design, transfer learning, and offline functionality to enhance accessibility and effectiveness in resource-constrained environments. Bahroun et al. synthesized key insights of GenAI in educational settings based on selecting 207 research papers through a bibliometric analysis. The study points out several meaningful implications for Educators, researchers, and policymakers. For Educators, GenAI could bring pedagogical innovation, creating interdisciplinary collaboration, but at the same time, Educators need to dive into the ethical implications of GenAI, e.g., in data privacy, biases, and academic integrity. D. Contribution of the Proposed Work This review highlights the role of ML in generating automated content, predicting student performance, and virtual teaching assistance. It contributes a structured overview of AI technologies integrated with pedagogical strategies, evaluating tools like rule-based chatbots, NLP systems, and decision trees for early dropout detection. This study delves into the potential applications of ML and its associated benefits, which can aid researchers in implementing AI-based educational systems. By integrating empirical studies with practical insights, this scoping review establishes a framework for AI literacy and ethical implementation in K-12 and tertiary education environments.

III. PROPOSED SYSTEM AND METHODOLOGY

A. System Architecture (Scoping Review Method) We performed a scoping review based on PRISMA-SCR guidelines. Since the field of the review (GenAI) is relatively new, we performed a scoping review instead of a systematic literature review (SLR). In addition, the nature of scoping reviews is exploratory aiming at rapidly mapping the key concepts in a research area. Scoping reviews summarize and disseminate research findings, identifying research gaps in the existing literature, or examining the range and nature of research activity. The architectural framework of the proposed ML educational system integrates various adaptive models. AI systems facilitate group formation based on cognitive diversity, enabling collaborative learning environments. Social constructivist approaches support metacognitive skill development through peer interaction. AI contributes to the development of educational, research, and management structures, which fosters a culture of innovation and internationalization in universities. B. System Design (Research Questions) To meet the objectives of this study, we proposed a set of research questions (RQs). RQ1: What are the bibliometric characteristics of the studies in terms of citations, journals, authors, and research topics? RQ2: What are the educational characteristics of the selected studies and their outcomes in the cognitive, affective, or behavioral learning domains? RQ3: What Gen IA integration strategies and activities have Educators and/or researchers constructed? RQ4: What are the challenges, issues, and opportunities for improvement of GenAI in engineering and computing education? For the study, we adopted an approach starting from the general features of the studies (bibliometric trends and research topics) and navigating towards their pedagogical particularities that help understand how Educators utilize GenAI in engineering and computing education from K-12 to tertiary levels. It is worth mentioning that this scoping review focuses on empirical research with evidence of application and evaluation whether or not the final educational results were positive or negative. C. Main System Modules (Identification of Studies) To identify relevant studies, we searched them in three databases: SCOPUS, Web of Science (WoS), and Education Resources Information Center (ERIC). Specifically, we included the terms "engineering education" and "computing education" with the tags in each database to search directly in the title, abstract, or keywords of every record obtained with the boolean connectors AND and OR. Regarding generative AI, we prefer not to include abbreviations such as GenAI or GAI since studies typically include the complete term, even in their indexing terms. Also, we do not add a specific timeframe because GenAI is relatively a new phenomenon. However, the studies retrieved are between 2022 and 2024. We obtained 146 records with this procedure. In the latter studies, we searched for

integration of GenAI in the educational settings in engineering and computing through an approach such as quantitative, qualitative, or mixed in any educational level (K-12 to tertiary). D. Data Integration (Screening and Appraisal Criteria) We downloaded the records of each database ($n = 146$) in the format of research information system (RIS). Then, these records were added to the software Rayyan.ai, which is a software specialized in the screening process for systematic and scoping reviews. With this software, firstly, we checked duplicates ($n = 14$), and secondly, we screened the ($n = 132$) remaining records. Nonetheless, ($n = 5$) articles could not be retrieved because the missing DOI or publisher was unavailable. Finally, ($n = 127$) records were retrieved. In addition, the studies must exhibit the development of any of the learning outcomes in the levels of cognitive (knowledge and skills), affective (attitudes, motivation), or behavioral (developed behaviors, e.g., socialization, communication, and organization skills), which are called domains of learning.

IV. IMPLEMENTATION DETAILS

A. Technology and Component Specification The implementation phase heavily relies on selecting optimal machine learning and natural language processing tools to facilitate automated learning environments. To respond to RQ1, VOSViewer v.1.6.14 and Crossref REST API were employed. VOSViewer is a software for bibliometric analysis based on network data that is focused on items and clusters with two overall functions: creating maps and visualizing them. VOSViewer was focused on the keywords of every study approved. Crossref REST API is a tool that allows the extraction of bibliometric information such as citations, authors, publishers, type of study (journal article, conference proceedings, book chapter), or articles per year, among others. The API was used with Python language to extract the bibliometric features of the studies. To respond to RQ2, we extracted information from each approved article such as study aim, research approach, participants, educational level, learning outcomes, and conclusions. To respond to RQ3, we identified some strategies and curricular activities described by the researchers in the learning settings. The information for RQ2 and RQ3 was coded using MAXQDA 24. We adopted the following procedure. Two researchers coded 640 fragments for the 24 studies, reading the articles and extracting the information. B. System Implementation (Bibliometric Characteristics) The trend shows an increase in proposals from 2023 to 2024 consistent with other prior systematic reviews. None proposals were identified for 2022. In 2023, the most cited article 'Unleashing ChatGPT's Power: A Case Study on Optimizing Information Retrieval in Flipped Classrooms via Prompt Engineering' describes a GenAI methodology with ChatGPT for computer science students, specifically, for the topic of TCP socket programming. Using the CRISPE framework, students could create more comprehensive and complete prompts to get in-depth information about the topics addressed. Another trend for this year is the concentration of proposals addressed from the teachers' perspective. These studies show the teachers' perceptions regarding GenAI, their possibilities, and the concerns related to their deployment in education. In 2024, the most cited article 'Prompt Problems: A New Programming Exercise for the Generative AI Era' deploys a GenAI methodology for CS1 and CS2. The methodology only offered visual representations of the problems, and students should use GenAI (ChatGPT) as a guide to achieve a solution. C. Dataset and API Configuration Of 24 studies analyzed, 11 proposals came from the U.S (45.83%), two proposals from the U.K. (8.33%), two proposals from Guatemala (8.33%), two proposals from Germany (8.33%), and countries such as New Zealand, Spain, Chile, Sweden, China, Finland, and Serbia each one with a proposal (4.16%) respectively. In the case of Guatemala, both proposals entail the teachers' perceptions regarding GenAI in computing and engineering education. Then, mainly, GenAI educational research has been led by the U.S. As for publication type in the studies, ($n = 19$, 82.6%) are conference proceedings while ($n = 5$, 21.74%) are journal articles. Most of the proposals were published in Association for Computing Machinery (ACM) conferences ($n = 11$, 48%) followed by IEEE ($n = 5$, 22%). This manifests the trend that the central part of the studies is related to computing education and computer science ($n = 17$); meanwhile, several proposals ($n = 7$) are for engineering education. D. Data Flow (Research Topics and Keywords) There are some noticeable aspects to remark regarding the cluster map for the keywords in the study. Firstly, AI literacy and AI pedagogy are related to arts, computing, and music for elementary school students. In the same cluster, AI literacy appears as a 21st-century skill to be developed by students. Also, for high school students, proposals describe a set of

activities to strengthen AI knowledge and literacy. Secondly, the computing education cluster is related to code generation, prompt engineering, conflict resolution, chatbots, and flipped classrooms. For instance, many studies for computing education in the ScR used GenAI tools for code generation, making that students paid attention to learning the logical structure of their programs and contrasting the new knowledge acquired by using GenAI with the prior one. Conversely, for the same feature of GenAI, researchers have reported problems, specifically, hallucinations and missing details and critical technical information in the case of ChatGPT. Seemingly, ChatGPT can work well with 'generic information' for CS1 and CS2 courses, but for more specific topics such as TCP sockets or encryption, retrieved information can fail, even providing wrong guidance.

V. RESULTS AND ANALYSIS

A. Test Cases (Educational Characteristics & Outcomes) We classified the synthesis into student-centered proposals and teacher-centered ones. We also divided the synthesis into several educational levels from K-12 to university. Readers can notice the prevalence of student-centered computing education proposals focused on cognitive learning outcomes at the university level. Nonetheless, for elementary and middle schools' students, there is an emphasis on affective learning outcomes. For K-12 levels, strategies explored how elementary-aged Latinx students historically excluded in CS establish connections between community, heritage, and technology using a text-to-image Generative AI (DALL.E). The qualitative focus groups showed that elementary students can make deeper connections when discussing imagined futures of their community and technology, creating prompts that embed technology into cultural practices. B. Performance Evaluation (Students' Perceptions) Reported positive tool-related perceptions from students are associated with the creative capability of GenAI to generate ideas and answers; personal tutoring with the features of convenient feedback and knowledgeable assistant; condensed and structured ways for programming purposes; support for students with limited experience in project management; debugging assistant and easy checking process for programming; support for decision-making process; massive, detailed, and immediate information availability; trustworthy information comparable to experts; and wiring catalyst in terms of improving professional writing style and concise and error-free language. In some proposals, students have reported the GenAI features of the help approach comparable to human interaction and not ego, not judgment referring that GenAI tools do not judge the type and level of questions that users do. Positive learning process perceptions from students include the discovery of new concepts and functions through understanding the logical structure of programs, the possibility to contrast previous knowledge with new information provided by GenAI, improving learning curve, developing analytical, problem-solving, computational, and innovative thinking, writing catalysis by improving writing skills, and enjoyment and engagement in activities. Concerning negative tool-related perceptions, students reported hallucinations in terms of difficulty in explaining ambiguous concepts, misinterpretation, slow processing, ignoring errors in programming, misleading suggestions, or inconsistent generative responses. Besides, repetitive and uncreative information; limited interpretation and analysis; unreliable and not trustworthy information for specific CS and engineering topics. In addition, students exposed the problem of weighting the answers given by the IA because the responses provided are generic and have not been reviewed. C. Discussion (Teachers' Perceptions) Teachers have indicated different tool-oriented possibilities and benefits such as support for the creation of personalized programming tasks, multiple approaches to validate students' comprehension, production of large and feasible software systems, an increase of productivity, and idea generation for learning activities, content generation, productivity with time optimization, and proof reading. From a pedagogical standpoint, teachers remark on the possibility that GenAI brings to rethinks and redesign the educational structure of courses through GenAI adaptation to learning goals, defining curriculum activities that incorporate GenAI, and change in traditional assessment. Nevertheless, teachers indicate several concerns and threats. For instance, teachers manifested the misbehavior practices that students could have such as cheating and plagiarism, violation of academic integrity rules, missing out the focus on learning, over-reliance which could hinder the development of skills, e.g., in fundamental programming concepts, lack of preparedness to cope with GenAI properly, and privacy, bias, and ethics issues. D. Comparative Analysis (GenAI Tools and Strategies) The typical role of GenAI tools was assistant for the learning process. Some of these strategies used their own personalized GenAI

chatbots, which were tailored to the particular learning goals in the courses. GenAI tools reported by the researchers in their methodologies include ChatGPT 3.5 and 4.0, DALL-E, Promptly (AI Web-based tool for visual representation of CS1 and CS2 problems designed by researchers), CS50 Duck (AI assistant tailored for introductory programming), GitHub Copilot, GAIPowered Slack Bot, Runway ML, AIVA, and Talking Head Anime from a Single Image 3. Instructional activities for K-12 levels are characterized by participatory sessions, some of them directed by questions such as the following: How do you use AI in your daily life? What are some interesting things you could do with AI? What are some potential use cases of AI? Also, some activities reported included creating a simple ML model using the 'Teachable Machine' platform development by Google. Concerning instructional activities for the tertiary level, these are featured by teaching topics in programming and engineering in which GenAI tools are used typically as assistants. Instructional activities include project-based learning, StandUp reports, Kata code approach, and feedback of students interactions.

VI. ALGORITHMS AND FRAMEWORKS

TABLE II

Algorithm/Technique	Application / Purpose
Ontologies and semantic networks	Structure domain and student knowledge, model relationships between concepts, and guide the selection of appropriate pedagogical strategies.
Rule-based systems	Utilize if-then rules to diagnose student errors and provide personalized feedback and hints based on individual actions.
Dialogue management	Interpret student questions and generate appropriate conversational responses to create an engaging, interactive learning experience.
Sentiment analysis	Analyze textual inputs to assess student emotions, enabling adaptive adjustments to the tutoring strategy based on affective cues.

TABLE III

Multimodal learning	Analyze diverse data (facial expressions, eye tracking, speech) to detect student emotions and adjust instructional methods accordingly.
Emotion recognition	Identify student emotions from facial expressions, speech, and physiological signals, allowing ITS to refine its tutoring strategies to better meet learners' emotional and cognitive needs.

TABLE IV

Tool Name	Technology & Features
Copyscape	AI and rule-based system to detect duplicated contents.
GPTZero	DL, statistical analysis to detect AI-generated content.
Grammarly	ML and NLP for AI writing detection and grammar check.
iThenticate	ML and NLP providing feedback on academic writing plagiarism.
Ouriginal	ML, text mining to detect plagiarism and improper citations.
Turnitin	ML and NLP for AI writing detection, feedback for academic writing plagiarism.

VII. LIMITATIONS AND ETHICAL CONSIDERATIONS

A. Privacy and Data Security One of the most pressing issues is privacy and data security. Adaptive learning systems and ITS collect extensive data about students, including academic performance, learning disabilities, and personal preferences. In some cases, AI systems may even track emotional states using facial recognition or sentiment analysis. If not properly secured, this data could be vulnerable to breaches or unauthorized access by third parties. Potential risks include data breaches leading to identity theft and surveillance concerns that may create a stifling 'Big Brother' effect, discouraging creativity and freedom of expression. Mitigation strategies include employing strong encryption methods, anonymizing data where possible, ensuring transparency regarding data collection and usage, and complying with regulations such as General Data Protection Regulation (GDPR) and (Family Educational Rights and Privacy Act) (FERPA). B. Bias and Fairness in AI Algorithms Another significant ethical challenge is bias and fairness in AI algorithms. AI systems rely on training data, and if that data contains historical biases, the algorithms may reinforce or even amplify existing inequalities. For instance, an adaptive learning system trained on biased data might recommend fewer advanced courses to students from underrepresented backgrounds, perpetuating disparities in educational opportunities. This issue poses risks such as reinforcing

inequities and limiting diversity in educational content. To mitigate bias, AI models should be trained on diverse datasets that represent a wide range of backgrounds, abilities, and learning styles. Regular bias audits should be conducted to assess fairness, and inclusive design principles should be applied, involving educators, students, and ethicists from diverse backgrounds to ensure AI-driven learning systems are equitable for all. C. Transparency and Accountability Transparency and accountability remain critical concerns in AI-driven education. Many AI algorithms function as 'black boxes,' meaning their decision-making processes are difficult for humans to interpret. This lack of transparency can lead to mistrust among educators, students, and parents who may not understand why specific recommendations or learning paths are suggested. Furthermore, accountability issues arise when AI systems make mistakes, such as misclassifying a student's skill level or recommending inappropriate content. Without clear responsibility, errors may go unaddressed, negatively impacting students' learning experiences. To address these challenges, AI developers should prioritize explainable AI to create systems that provide clear justifications for their decisions. D. Student Autonomy and AI Dependency The increasing use of AI in education raises concerns about student autonomy and the risk of overdependence on AI-driven tools. While AI can enhance efficiency by providing instant answers and personalized recommendations, excessive reliance on these tools may reduce critical thinking and problem-solving skills. For example, AI-powered homework assistants like ChatGPT and Wolfram Alpha can quickly solve complex problems, but if students passively accept AI-generated answers without attempting to understand the underlying concepts, their cognitive development may suffer. To mitigate this, educators should encourage students to use AI as a learning aid rather than a substitute for independent thought. Assignments that require students to explain their reasoning and engage in discussions can help balance AI support with critical thinking development. E. Digital Divide and Accessibility AI-powered personalized learning promises to expand access to high-quality education, but it also risks widening the digital divide. Students in well-funded schools with reliable internet and advanced devices can fully leverage AI-driven education, while those in underprivileged areas may struggle due to limited access to technology. AI-powered smart classrooms and VR-based learning experiences, for example, provide immersive and interactive education, but they remain inaccessible to many due to cost barriers. To ensure equitable learning opportunities, governments and institutions must invest in affordable AI-driven educational tools and improve digital infrastructure in low-income regions. Additionally, developing AI models that function effectively in low-resource environments, such as mobile-friendly AI tutors that work offline, can help bridge the gap in accessibility. F. Ethical AI Usage in Students' Evaluations AI is increasingly being used for student evaluations, from automated grading to predictive analytics that assess a student's likelihood of success or dropout risk. While these systems offer efficiency and early intervention for struggling students, they also raise ethical concerns related to fairness and bias. AI-based student analytics can sometimes reflect historical inequalities, leading to unintended biases in recommendations. For example, if an AI system predicts lower performance for students from marginalized backgrounds based on past data, it may limit their access to advanced coursework or enrichment opportunities. To prevent such biases, AI models should be trained on diverse datasets that represent students from all backgrounds. Regular bias audits, along with a collaborative approach where teachers review AI-generated evaluations, can ensure that assessments are fair, inclusive, and supportive of student growth. G. Overall Educational Limitations We observed several issues and challenges regarding the pedagogical component of GenAI. There is an overestimation of students and teachers' perceptions regarding Gen AI tools but an underestimation of how Gen AI tools influence the teaching-learning process. We observe that many studies are focused on perceptions, but few report how GenAI tools benefit students' learning process, and how these tools are aligned with the skills and outcomes expected in the curricula of engineering and computing. There is no balance between the number of student-centered and teacher-centered proposals. It is missing the standpoint and criteria of teachers as co-creators of Gen AI methodologies. In fact, we did not identify educational programs focused on teachers' formation to effectively cope with Gen AI. AI literacy competencies are ambiguous. For instance, some AI literacy competencies proposed can work with the tertiary level (university) and not with K-12 ones, e.g., when we explain LLMs from a technical perspective. Then, it is unclear what learning outcomes and skills are expected to be developed by students with Gen AI at different educational levels.

VIII. FUTURE SCOPE

A. Emerging Applications of ML and AI in Education AI and ML in education will provide new teaching and assessment opportunities. Some interesting new applications include educational content generation, personalized learning, smart advising systems, assessment grading automation, and interactive class collaboration. Educational Content Generation: Generative AI can reshape various educational content, such as developing higher education curricula. LLMs can effectively analyze responses, provide constructive feedback, and identify subtle comprehension issues or misunderstandings. Studies demonstrating automated production of quizzes set a precedent for future research in the automated production of educational content in multiple languages. Personalized Learning: AI may improve access to education, collaborative spaces, and intelligent tutoring tools to help instructors and personalize learning. AI is an innovative way for special education teachers to fulfill responsibilities, used in predictive text, adaptive learning systems, and digital assistants. Mixing technology with conventional teaching techniques improves learning. Developing evidence-based Generative AI integration standards and regulations, encouraging critical thinking and digital literacy in students, and promoting responsible AI use in higher education are essential. Smart Advising Systems: Smart advising systems are an essential use of AI and ML in education, providing students with individualized help throughout their academic experience. These systems use data analytics, predictive modeling, and NLP to make personalized suggestions about course choices, career paths, and academic performance enhancement. A recommendation system for advisors and students that evaluates student data to create tailored study programs over several semesters amalgamates concepts from graph theory, performance modeling, ML, and explainable suggestions. B. Continuous Evaluation and Teacher Involvement We need to reflect on 'learning by doing' during the whole process of using Gen AI. Many proposals only identified the students perceptions once the process finished and not before. The observation concerning students' interaction should be throughout the educational process to measure the value of GenAI in creating meaningful learning. In this, positive and negative outcomes derived from GenAI usage should be analyzed. A better conceptualization of AI literacy and its competencies should be provided. Yet, this term and what it means for engineering and computing education is in an early development stage. A proper conceptualization for engineering and computing should be created, analyzing the sociocultural context and the implications of GenAI in the curricula. Teachers' voices must be considered in the whole process of educational co-creation with GenAI. Here, the teachers' formation must be crucial for leveraging and properly integrating GenAI tools in the teaching-learning process. We distinguish between the formation in Gen AI usage and the pedagogical formation to deploy it effectively in the learning settings.

IX. CONCLUSION

This scoping review analyzed and described GenAI methodologies and strategies for engineering and computing education. We identified twenty-four empirical proposals, most of them for computing education at the tertiary level with few for K-12 levels. At the same time, we detected that the central part of the proposals is describing students' and teachers' perceptions and affordances of GenAI tools dominated by ChatGPT. Only a few studies describe methodologies with evidence-based outcomes from quantitative, qualitative, or mixed approaches. Then, it is tough to analyze how GenAI intervenes in the learning process from cognitive, affective, or behavioral domains, including sociocultural and identity aspects of students. Another aspect that we consider crucial to expose is that teachers' voices are missing out. Most of the proposals are student-centered and have diverse outcomes. Still, the standpoints of the teachers and formation programs for them in GenAI at the technical and pedagogical levels are missing. Several studies asserted this issue as significant to the successful leverage of GenAI in learning settings. It seems that in the discourse, GenAI tools by themselves were self-described and self-explanatory for students when evidence shows just the opposite: Students can struggle with AI-based systems and prompt engineering, even when considered digital natives. Teacher support is essential to unveil the implications of GenAI in engineering and computing

education. Similarly, extant literature remarks on two concepts: AI literacy and prompt engineering. On one hand, seemingly, AI literacy and prompt engineering do not have a close relationship or correlation. This indicates that students can learn how to make prompts without even knowing about AI literacy. The previous aspects point out that is necessary to take a critical pedagogical perspective of GenAI systems, and we need to think beyond the GenAI hype. GenAI is only a tool that should be oriented towards our pedagogical purposes and not vice versa. We encourage educators and researchers to take the outcomes and findings of this ScR to co-create methodologies, frameworks, and critical positions about what GenAI means and entails for engineering and computing education.

TABLE I	
Algorithm/Technique	Application / Purpose
Bayesian Networks	Model a learner's knowledge state and predict future success, dynamically adjusting question difficulty based on inferred mastery levels.
Item Response Theory	Select optimally challenging items by analyzing the probability of a correct response based on learner ability and item difficulty, enhancing assessment efficiency.
Reinforcement Learning	Dynamically adjust learning paths through trial- and-error, using reward signals to optimize learner engagement and performance based on real-time interactions and feedback.
Collaborative filtering	Recommend relevant learning materials by analyzing user preferences and behaviors of similar learners, thereby personalizing content suggestions.
Deep Learning	Analyze complex interaction patterns in learner data to provide personalized content recommendations, predict performance, and detect learning difficulties with high accuracy.
Decision Tree	Classify students into different learning styles and generate personalized learning paths by creating data-driven rules for student segmentation.
Knowledge tracing	Monitor and predict the evolution of a learner's knowledge over time, informing the selection of future questions based on historical performance and mastery of concepts.

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